REMARKS

Claim Rejections – 35 U.S.C. § 102(a)

In the Office Action dated September 10, 2004, claims 1-12 stand finally rejected as anticipated by, Pennington, W., *Calibration of Seismic Attributes for Reservoir Characterization*, Annual Report, DOE Award No. DE-AC26-98BC15135 (Pennington).

The Applicant respectfully submits herewith a Second Declaration of M. Turhan Taner which establishes conception of the claimed invention and reduction to practice prior to the effective date of Pennington as prior art under 35 U.S.C. § 102(a). The Applicant does not, by submitting the Declaration, admit that the disclosure of Pennington is within the scope of the Applicant's claims.

In the Office Action dated September 10, 2004, it was stated that a previously filed Declaration of M. Turhan Taner was not sufficient proof of conception of the claimed invention, more specifically, that the Declaration was not "relevant" to the claims. The Applicant's Second Declaration is intended to be responsive to that specific issue.

In particular, claim 1 recites a method of geophysical exploration including:

> a) organizing seismic data using an unsupervised learning network;
> b) correlating a portion of the organized seismic data with lithological data from a wellbore located in a subsurface region of interest, and
> c) applying the correlation to the seismic data to estimate lithology in the subsurface region of interest.

Clearly, the first Declaration establishes that the Applicant conceived of organizing seismic data using an unsupervised learning network. The Kohonen self-organizing map technique is one embodiment of such organization. In the Office Action of September 10, 2004, it was stated that the claimed "correlating" the organized seismic data to lithology was not proven as conceived by the Declaration. The Second Declaration is intended to be responsive to this point, to the extent the first Declaration does not already make such proof. The Declarant (Applicant) clearly has shown conception and reduction to practice of calibration of organized seismic data to lithology. Applicant respectfully points out that "calibration" is in fact one form

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of "correlation", specifically, correlating a measurement to a standard. As evidence of the foregoing statement, Applicant respectfully submits herewith definitions from *Merriam-Webster Online* definitions of "calibrate", meaning among other things, "to adjust precisely for a particular function" and "correlate", meaning among other things "to present or set forth as to show the relationship." Clearly, a person of ordinary skill in the art, having the benefit of the Applicant's disclosure, would understand that "calibration" as stated in the Declarations and in the Applicant's specification supporting documentation fully enables "correlation" of lithology from wellbore data to organized seismic data as recited in Applicant's claim 1.

Thus, the Second Declaration of M. Turhan Taner establishes that not later than January 2001, source code had been written, and described to colleagues of the Applicant which performed the steps of: organizing seismic data using an unsupervised learning network; calibrating the organized seismic data using lithology data from wellbores, and using the calibrated seismic data to infer lithology.

The Applicant believes that this Reply is fully responsive to the ground of rejection stated in the Office Action of September 10, 2004, and respectfully requests early favorable action on this application.

Respectfully submitted,

Date: 12/12/2003

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IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Applicant :	Taner, M. et al.	Art Unit :	2863
Serial No.:	10/035,955	Examiner :	Le, T.
		Docket No.:	RSI-003

Filed : 12/24/2001
Title : SYSTEM FOR UTILIZING SEISMIC DATA TO ESTIMATE SUBSURFACE LITHOLOGY

Commissioner for Patents
P. O. Box 1450
Alexandria, VA 22313-1450

SECOND DECLARATION OF M. TURHAN TANER

M. Turhan Taner declares that:

I am currently employed by and have been employed by RDSP I, LP, the assignee of all right, title and interest in the referenced patent application since 1994 as a research geophysicist. I have published numerous papers on the subject of seismic attributes and their application to interpretation of seismic data. I am the same person who authored a publication cited in an Office Action dated November 6, 2003 in the referenced patent application entitled, *Kohonen's Self-Organizing Networks With "Conscience"*, Seismic Research Corporation. I have worked on various research projects related to Kohonen self-organizing maps since at least the time of publication of the foregoing publication.

During late 1999, and in the regular course of my employment with RDSP I, LP, I conceived of a way to calibrate self organizing map clusters for use in reservoir characterization. I worked on a number of experimental computer programs intended to embody the concept. A result of my development work is memorialized in a report for internal review at RDSP I, LP entitled, *Calibration of Self-Organizing Maps*, produced in November 2000. A copy of that report was previously submitted for consideration by the Patent and Trademark Office in a Reply filed to the Office Action of July 1, 2004. The report expressly explains a calibration method for providing a relationship between each self organized map and wellbore-measured lithology.

Experimental computer source code intended to embody the calibration method described in the above report was generated as early as February 2000, and was revised to improve its performance in January 2001. A copy of relevant portions of the source code showing the various calibration routines is attached as Exhibit A.

At about the same time the lithology calibration technique was developed by me, I also used such lithology-calibrated Kohonen self-organized maps to infer reservoir properties from seismic data. A presentation of such application was made to colleagues from my employer during January 2001. A copy of slides from the presentation, clearly showing lithology-calibrated seismic data used to infer reservoir properties from such seismic data, is attached as Exhibit B. The slides relating to "reservoir characterization" shown in the presentation in Exhibit B are graphic displays of a number of properties of a subsurface reservoir, including mineral composition of the reservoir rock, which is referred to as "lithology"; fractional volume of pore space in the rock, referred to as "porosity", and fluid content of the rock in terms of hydrocarbon and water fractional volumes filling the pore space.

All statements made herein of my own knowledge are true, and all statements made on information and belief are believed to be true. Further, these statements are made with the knowledge that willful false statements and the like are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code and may jeopardize the validity of the application or any patent issued thereon.

Respectfully submitted,

M. Turhan Taner

M. Turhan Taner

EXHIBIT A

```
C***********************************************************************
        SUBROUTINE  RBF_CALIB(CLAS, ATRIB, NOATR, NDTA, NCLAS,
     *                        SOFM, NOXX, NOYY, MAPS,HDOUT,
     *                        NOSOM,GAUS,WEG,CLANO, TEM,DOUT,CLASSX,
     *                        ISTAT)
C
C***********************************************************************
**
C
      IMPLICIT NONE
      SAVE
C
C+RBF_CALIB
C
C-FUNCTION:   THIS SUBROUTINE CALIBRATES THE UNSUPERVISED CLUSTERING
C                    BASED ON GIVEN CLAS BORE MEASUREMENTS
C                   BY RADIAL BASIS FUNCTION NETWORK LOGIC
C
C-CALLING SEQUENCE:
C
C            CALL RBF_CALIB(CLAS,SOFM,NDTA,NOXX,NOYY ....)
C
C-ARGUMENTS:
C
C  CLAS(*)  = WELL BORE LITHOLOGY OR RESERVOIR CLASSIFICATION NUMBER
C  ATRIB(*) = ATTRIBUTES CORRESPONDING EACH WELL BORE SAMPLES
C  NOATR    = NUMBER OF ATTRIBUTE  SAME NUMBER AS SOM COEFFICIENTS)
C  NDTA     = NUMBER OF WELL BORE SAMPLES
C  NCLAS    = TOTAL NUMBER OF WELL BORE CLASSES
C  SOFM(*)  = SELF ORGANIZING FEATURE MAP CLUSTER COEFFICIENTS
C             WELL BORE CLASSIFICATION NUMBER.
C  NOXX     = NUMBER OF NEURONS IN X DIRECTION.
C  NOYY     = NUMBER OF NEURONS IN Y DIRECTION
C  MAPS     = KOHONEN MAP TYPE. ( 1 = ONE D, 2 = RECTANGULAR, 3
=TRIANGULAR)
C
C--- TEM(*) = TEMPORARY STORAGE AREA  , IT SHOULD BE AT LEAST 6*NOSOM
LING
C
C----- OUTPUT ---------
C
C  HDOUT(I) = HIDDEN LAYER OUTPUT FROM EACH NEURON FOR ALL THE TRAINING
DATA
C             SAMPLES. ARRAY WILL BE NOXX8NOYY*NDTA SAMPLES LONG.
C  NOSOM    = TOTAL NUMBER OF SOM NEURONS,
C  GAUS(*)  = SHAPING FACTORS OF SOM NEURONS GAUSSIAN SHAPE RADIAL
FUNCTION
C  WEG(*)   = OUTPUT LAYER WEIGHTS FOR EACH OUTPUT NEURON ( EACH NOSOM
ELEMENTS)
C  CLANO(*) = USER ASSIGNED CLASS NUMBER FOR EACH OUTPUT NEURON (NCLAS
LONG)
C  DOUT(*)  = DESIRED OUTPUT ARRAY (NDTA)
C
C-DESCRIPTION:
C
C    BIG LOOP IS ON EACH LITHOLOGY CLASS;(OPTIMIZED SEPARATELY)
C    IN THE FIRST PASS WE WILL ESTABLISH AVERAGE DISTANCES TO EACH SOM
C    NEURON. THIS WILL CONTROL( GAUSSIAN ) RADIAL BASIS FUNCTION SHAPE.
C    FOR EACH LITHOLOGY CLASS, THE EUCLIDEAN DISTANCE WILL BE COMPUTED
C    BETWEEN EACH TRAINING DATA SAMPLE ( CONSISTING OF ATTRIBUTES PICKED
C    FROM THE VICINITY OF WELLS) AND EACH NEURON. THIS WILL BE INPUT TO
```

```
C    THE RADIAL BASIS FUNCTIONS OF THE NEURON, WHICH WILL PRODUCE THE
C    OUTPUT OF THE HIDDEN LAYER. THESE OUTPUTS WILL BE THE INPUT TO THE
C    OUTPUT LAYER NEURONS.
C    WEIGHTS OF THE OUTPUT LAYER NEURONS WILL BE COMPUTED ONE CLASS AT A
C    TIME BY THE WIENER FILTER LMS METHOD.
C    COMPUTATION WILL BE REPEATED FOR EACH INDIVIDUAL LITHOLOGY CLASS.
C
C-REVISED:  27-FEBRUARY-2000     BY    M. TURHAN TANER
C-REVISED:  16-FEBRUARY-2001     BY    M. TURHAN TANER , DAVID DUMAS
C-REVISED:   1-AUGUST  -2001     BY    M. TURHAN TANER , DAVID DUMAS
C
C
C++
C
      INTEGER*4   NOXX,NOYY, MAPS, NDTA,NCLAS, MITER, NITER
      INTEGER*4   I, IS, IP,IK, NOSOM,ICL,NOATR,J,K,ICO,IPC
      INTEGER*4   IK1,IK2,IK3,IK4,IK5,IW
      INTEGER*4   IT,LAST,STATUS,ISTAT

      REAL*4      CLAS(1:*), PCLAS(200),HDOUT(1:*),GAUS(1:*)
      REAL*4      SOFM(1:*), ATRIB(1:*),DISAV,DIST,WEG(1:*)
      REAL*4      AA,CLANO(1:*),AMIN,RRAT,DOUT(1:*)
      REAL*4      CLASSX(1:*)
      REAL*4      TEM(1:*)
C
C------ INITIALIZE COMPUTATION CONSTANTS
C
           NOSOM = NOXX
        IF(MAPS .EQ. 2 )  NOSOM = NOXX*NOYY
        IF(MAPS .EQ. 3 )  NOSOM = NOXX*(NOXX+1)/2
        IK1 = 1
        IK2 = IK1 + NOSOM
        IK3 = IK2 + NOSOM
        IK4 = IK3 + NOSOM
        IK5 = IK4 + NOSOM
        NITER = 20
        MITER = 10
        RRAT  = 0.00001
        LAST  = (NOSOM+1)*10
C
C++++++++++ CALCULATE AVERAGE EUCLIDEAN DISTANCE BETWEEN CALIBRATION
C                     DATA AND  SOM NEURONS
C
        DO    I = 1, NOSOM
            GAUS(I)  = 0.
            PCLAS(I) = 0.
        ENDDO
            DISAV = 0.0
        DO   300         ICL = 1, NDTA
            DIST = 99999999.
            ICO  = 0
            IPC  = (ICL-1)*NOATR
          DO        I = 1, NOSOM
            IS = (I-1)*NOATR
            AA = 0.0
            DO   J =1, NOATR
              AA = AA+(ATRIB(IPC+J)-SOFM(IS+J))**2
            ENDDO
              IF( AA .LT. DIST ) THEN
                  DIST = AA
                   ICO = I
```

```
C***********************************************************************
*
       SUBROUTINE  CALERR( IWELL, ATRIB, NOATR, NWELL, NOCLASS,
     *                     SOFM, NOXX, NOYY, MAPS,
     *                     CALIB, PCLAS, CERR,CPROB,NOERR,
     *                     TOTAL,CLASS)
C
C***********************************************************************
**
C
      IMPLICIT NONE
      SAVE
C
C+CALERR
C
C-FUNCTION:   THIS SUBROUTINE COMPUTES CALIBRATION ERROR OF SOM
C                     BASED ON GIVEN WELL BORE MEASUREMENTS
C                     BY GENERATING MAXIMUM PROBABILITY
C
C-CALLING SEQUENCE:
C
C             CALL CALERR(IWELL,ATRIB,NOATR,NWELL,....)
C
C-ARGUMENTS:
C
C  IWELL(*) = WELL BORE LITHOLOGY OR RESERVOIR CLASSIFICATION NUMBER
C  ATRIB(*) = ATTRIBUTES CORRESPONDING EACH WELL BORE SAMPLES
C  NOATR    = NUMBER OF ATTRIBUTE  SAME NUMBER AS SOM COEFFICIENTS)
C  NWELL    = NUMBER OF WELL BORE SAMPLES
C  NOCLASS  - TOTAL NUMBER OF WELL BORE CLASSES
C  SOFM(*)  = SELF ORGANIZING FEATURE MAP CLUSTER COEFFICIENTS
C             WELL BORE CLASSIFICATION NUMBER.
C  NOXX     = NUMBER OF NEURONS IN X DIRECTION.
C  NOYY     = NUMBER OF NEURONS IN Y DIRECTION
C  MAPS     = KOHONEN MAP TYPE. ( 1 = ONE D, 2 = RECTANGULAR, 3
=TRIANGULAR)
C  CALIB(*) = WELL BORE LITHOLOGY CLASSES OF EACH INPUT SOM NEURON
C  CLASS(*) = CLASSIFICATION FROM SELFORG FOR UNDEFINE VALUES
C
C----- OUTPUT ---------
C
C              NOTE: OUTPUT ARRAYS WILL BE "NWELL" LONG AND THEY WILL
C              CORRESPOND TO EACH TRAINING DATA SAMPLK.
C
C  PCLAS(*) = PREDICTED CLASS ACCORDING TO THE CALIBRATION
C  CERR(*)  = ERROR OF CLASSIFICATION ( DIFFERENCE BETWEEN PREDICTED AND
C             ACTUAL CLASSES
C  CPROB(*) = EUCLIDEAN DISTANCE BETWEEN NEAREST NEURAN AND THE DATA
C  NOERR(*) = TOTAL NUMBER OF ERRONEOUS CLASSIFICATIONS OF EACH SOM
NODE.
C  TOTAL(*) = TOTAL PICKS AT A NODE
C
C-DESCRIPTION:
C
C    BIG LOOP IS ON EACH LITHOLOGY CLASS;
C    FOR EACH LITHOLOGY CLASS, EACH DATA SAMPLE ( CONSISTING OF
ATTRIBUTES
C    PICKED FROM THE VICINITY OF WELLS) VECTOR DOT PRODUCT WILL BE
COMPUTED.
C    WITH EACH NEURON. THE INPUT DATA WILL BE CLASSIFIED BELONGING TO
THE
```

```
C    SAME CLASS OF THE CALIBRATED NEURON.
C
C-REVISED:  20-FEBRUARY-2000     BY   M. TURHAN TANER
C-REVISED:  16-JANUARY -2001     BY   M. TURHAN TANER , DAVID DUMAS
C
C
C++
C
      INTEGER*4    NOXX,NOYY, MAPS, NWELL,NOCLASS, NOERR(1:*)
      INTEGER*4    I, IS, NOSOM,ICL,NOATR,J,ICLAS,TOTAL(1:*)

      REAL*4       IWELL(1:*), PCLAS(1:*), CALIB(1:*),CPROB(1:*)
      REAL*4       SOFM(1:*), IPC,ATRIB(1:*),DIST
      REAL*4       AA, CERR(1:*),CLASS(1:*),LAST
C
C------ INITIALIZE COMPUTATION CONSTANTS
C
           NOSOM = NOXX
        IF(MAPS .EQ. 2 )   NOSOM = NOXX*NOYY
        IF(MAPS .EQ. 3 )   NOSOM = NOXX*(NOXX+1)/2
        LAST = (NOSOM+1)*10
C
C++++++++++ CALCULATE ECLIDEAN DISTANCE BETWEEN CALIBRATION
C                 DATA AND  SOM NEURONS
C
        DO   I = 1, NOSOM
            NOERR(I) = 0
            TOTAL(I) = 0
        ENDDO
        DO   I = 1,NWELL
            CPROB(I) = 0.0
            PCLAS(I) = 0.0
            CERR(I)  = 0.0
        ENDDO
        DO   300        ICL = 1, NWELL
            DIST   = 99999999.
            ICLAS = 0
            IPC   = (ICL-1)*NOATR
          DO        I = 1, NOSOM
            IS = (I-1)*NOATR
            AA = 0.0
            DO   J =1, NOATR
              AA = AA+(ATRIB(IPC+J)-SOFM(IS+J))**2
            ENDDO
              IF( AA .LT. DIST ) THEN
                DIST = AA
                ICLAS= I
              ENDIF
          ENDDO
C
C------ CHECK IF CLASSIFICATION MATCHES THE CALIBRATED CLASS
C
         CPROB(ICL) = DIST
         PCLAS(ICL) = 0.
         IF(CLASS(ICLAS).LT.LAST.AND.CALIB(ICLAS).GT.0.0) THEN
             PCLAS(ICL) = CALIB(ICLAS)
         ENDIF
         IF(IWELL(ICL).GT.0..AND.CLASS(ICLAS).LT.LAST) THEN
             TOTAL(ICLAS) = TOTAL(ICLAS)+1
             CERR(ICL)   = IWELL(ICL) - PCLAS(ICL)
             IF( CERR(ICL) .NE. 0.0) NOERR(ICLAS) = NOERR(ICLAS) + 1
```

```
C***********************************************************************
        SUBROUTINE  CALPROB ( IWELL, ATRIB, NOATR, NWELL, NOCLASS,
     *                        SOFM, NOXX, NOYY, MAPS,
     *                        CALIB, PROB,SDISA,SCALE,NITR,PAVE,WEG,
     *                        CLASS )
C
C***********************************************************************
**
C
      IMPLICIT NONE
      SAVE
C
C+CALIBRT
C
C-FUNCTION:   THIS SUBROUTINE CALIBRATES THE UNSUPERVISED CLUSTERING
C                     BASED ON GIVEN WELL BORE MEASUREMENTS
C                     BY GENERATING MAXIMUM PROBABILITY
C
C-CALLING SEQUENCE:
C
C            CALL CALPROB(WELL,SOFM,NWELL,NOXX,NOYY ....)
C
C-ARGUMENTS:
C
C  IWELL(*) = WELL BORE LITHOLOGY OR RESERVOIR CLASSIFICATION NUMBER
C  ATRIB(*) = ATTRIBUTES CORRESPONDING EACH WELL BORE SAMPLES
C  NOATR    = NUMBER OF ATTRIBUTE  SAME NUMBER AS SOM COEFFICIENTS)
C  NWELL    = NUMBER OF WELL BORE SAMPLES
C  NOCLASS  - TOTAL NUMBER OF WELL BORE CLASSES
C  SOFM(*)  = SELF ORGANIZING FEATURE MAP CLUSTER COEFFICIENTS
C             WELL BORE CLASSIFICATION NUMBER.
C  NOXX     = NUMBER OF NEURONS IN X DIRECTION.
C  NOYY     = NUMBER OF NEURONS IN Y DIRECTION
C  MAPS     = KOHONEN MAP TYPE. ( 1 = ONE D, 2 = RECTANGULAR, 3
=TRIANGULAR)
C
C----- OUTPUT ---------
C
C  CALIB(I) = WELL BORE LITHOLOGY CLASSES OF EACH INPUT SOM NEURON
C  PROB(I)  + PROBABILITY OF EACH CALIBRATION ( 0<PROB<100 )
C
C-DESCRIPTION:
C
C    BIG LOOP IS ON EACH LITHOLOGY CLASS;
C    FOR EACH LITHOLOGY CLASS, EACH DATA SAMPLE ( CONSISTING OF
ATTRIBUTES
C    PICKED FROM THE VICINITY OF WELLS) VECTOR DOT PRODUCT WILL BE
COMPUTED.
C    WITH EACH NEURON. THIS WILL BE THE PROBABILITY OF EACH DATA POINT.
C    THESE VALUES WILL BE ACCUMULATED FOR ALL DATA POINTS FOR THAT CLASS
AND
C    RESULTS WILL BE DIVIDED BY THE NUMBER OF POINTS. THIS WILL
CONSTITUTE
C    THE PROBABILITY OF THAT CLASS.
C    NEXT WE WILL USE BAYESIAN LOGIC, THAT IS COMPARE THIS PROBABILITY
FUNCTION
C    WITH THE STORED MAXIMUM PROBABILITY FUNCTION OF PREVIOUS
COMPUTATIONS.
C    FOR EACH NEURON, IF THE NEW ONE IS LESS THAN PREVIOUS ONE, THEN GO
TO THE
C    NEXT NEURON. IF GREATER , THEN UPDATE THE MAXIMUM PROBABILITY AND
```

```
SET THE
C     NEW CLASS NUMBER ON THE LIST FOR THAT NEURON.
C     REPEAT THIS FOR ALL THE CLASSES. AT THE END, WE WILL HAVE TWO
TABLE,
C     SIMILAR TO THE KOHONEN MAP; ONE CLASS ASSIGNMENT FOR EACH NEURON,
AND
C     THE SECOND ONE PROBABILITY OF THAT CLASS ASSIGNMENT. THESE TABLES
WILL
C     LATER BE USED FOR (CALIBRATED) CLASSIFICATION OF THE WHOLE DATA
VOLUME.
C
C-REVISED:  20-FEBRUARY-2000     BY    M. TURHAN TANER & NAUM DERZHI
C-REVISED:  16-JANUARY -2001     BY    M. TURHAN TANER
C
C
C++
C
      INTEGER*4   NOXX,NOYY, MAPS, NWELL,NOCLASS, ITER
      INTEGER*4   I, M, IS, NOSOM,ICL,NOATR,KATR,K
      INTEGER*4   NITR,ISO,J,IMM,NUMWELL

      REAL*4      IWELL(1:*), PCLAS(200,40), CALIB(1:*), PROB(1:*)
      REAL*4      SOFM(1:*), IPC,NXCL,ATRIB(1:*),WG,ALPA
      REAL*4      AA,BETA,APC, SDISA, PAVE(1:NOXX,1:NOCLASS)
      REAL*4      WEG(1:NOXX,1:NOCLASS),DISAV,DIST
      REAL*4      SCALE,CLASS(1:*),LAST,ADD,JCLASS(100)
C
C------ INITIALIZE COMPUTATION CONSTANTS
C
           NOSOM = NOXX
        IF(NITR.LT.1) NITR = 1
        IF(NITR.GT.4) NITR = 4
        LAST = (NOSOM+1)*10.
C
C++++++++++ CCALCULATE AVERAGE ECLIDEAN DISTANCE BETWEEN CALIBRATION
C                     DATA AND  SOM NEURONS
            DISAV = 0.0
            NUMWELL = 0
        DO   300        ICL = 1, NWELL
            IF(IWELL(ICL).LT.0.0) GOTO 300
            DIST = 99999999.
            IMM  = (ICL-1)*NOATR
          DO        I = 1, NOSOM
            IS = (I-1)*NOATR
            AA = 0.0
            DO   J =1, NOATR
              AA = AA+(ATRIB(IMM+J)-SOFM(IS+J))**2
            ENDDO
              IF( AA .LT. DIST ) DIST = AA
          ENDDO
            DISAV = DISAV + DIST
            NUMWELL = NUMWELL+1
300     CONTINUE
C
C-------- AVERAGE DISTANCE (SQUARE)
C
          DISAV = DISAV/NUMWELL
          DISAV = DISAV*SCALE*SCALE
          ALPA  = ALOG(0.5)/DISAV
          SDISA = SQRT(DISAV)
C
```

EXHIBIT B

Palm Dictionary
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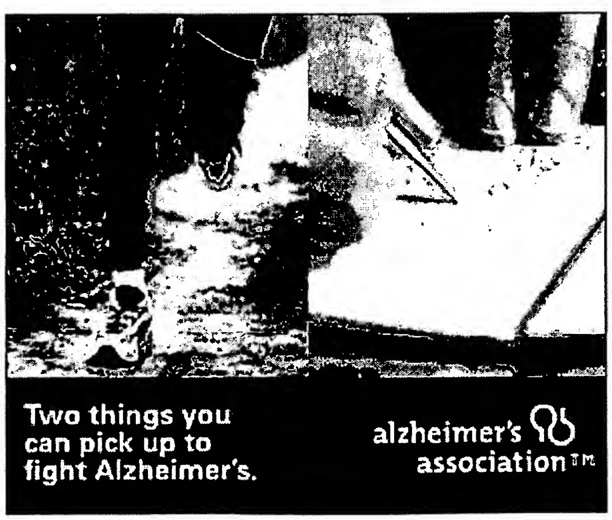
Merriam-Webster Online Dictionary

One entry found for **calibrate**.

Main Entry: **cal·i·brate**
Pronunciation: 'ka-l&-"brAt
Function: *transitive verb*
Inflected Form(s): **-brat·ed**; **-brat·ing**
1 : to ascertain the caliber of (as a thermometer tube)
2 : to determine, rectify, or mark the graduations of (as a thermometer tube)
3 : to standardize (as a measuring instrument) by determining the deviation from a standard so as to ascertain the proper correction factors
4 : to adjust precisely for a particular function
- **cal·i·bra·tor** /-"brA-t&r/ *noun*

For More Information on "calibrate" go to Britannica.com
Get the Top 10 Search Results for "calibrate"



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Thesaurus

2 entries found for **correlate**.
To select an entry, click on it.

correlate[1,noun]
correlate[2,verb]
Go

Main Entry: **^{2}cor·re·late**
Pronunciation: -"lAt
Function: *verb*
Inflected Form(s): **-lat·ed; -lat·ing**
intransitive senses **:** to bear reciprocal or mutual relations **:** CORRESPOND
transitive senses
1 a : to establish a mutual or reciprocal relation between <*correlate* activities in the lab and the field> **b :** to show correlation or a causal relationship between
2 : to present or set forth so as to show relationship <he *correlates* the findings of the scientists, the psychologists, and the mystics -- Eugene Exman>
- **cor·re·lat·able** /-"lA-t&-b&l/ *adjective*
- **cor·re·lat·or** /-"lA-t&r/ *noun*

For More Information on "correlate" go to Britannica.com

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Merriam-Webster Online Dictionary

Thesaurus

One entry found for **correspond**.

Main Entry: **cor·re·spond**
Pronunciation: "kor-&-'spänd, "kär-
Function: *intransitive verb*
Etymology: Middle French or Medieval Latin; Middle French *correspondre,* from Medieval Latin *correspondEre,* from Latin *com-* + *respondEre* to respond
1 a : to be in conformity or agreement <the ideal failed... to *correspond* with the reality -- J. R. Sutherland> **b :** to compare closely **:** MATCH -- usually used with *to* or *with* **c :** to be equivalent or parallel
2 : to communicate with a person by exchange of letters

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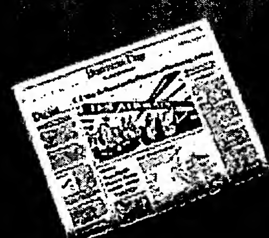

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Pronunciation Symbols

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Kohonen's Self Organizing Maps Application and Calibration

M. Turhan Taner, David Dumas &
Naum Derzhi
Rock Solid Images

Brunello
Di
Montalcino

Prof. Teuvo Kohonen

OBJECTIVE:

- The Objective is to determine estimates of reservoirs rock and fluid properties by seismically driven measurement.
- Seismically measured entities are the Seismic Attributes
- Relationship between Seismic Attributes and the reservoir properties are complicated
- Neural Networks are convenient tools in complicated cases.

Artificial Neural Networks

- They behave like Non-linear Wiener filters
- They learn by experience, can be supervised or unsupervised
- Input could be traces or combination of attributes in vectorial form
- They can predict or classify according to the knowledge they gained in the training.

Classification

- Classification is the division of a given set of objects into different groups based on their discriminating features.
- Discriminating features are those that maximize the differences between each group.
- In seismic event classification the discriminating features are the seismic attributes.

Classification via Artificial Neural Networks

- Unsupervised Classification:
  - Kohonen's Self Organizing Feature Maps
- Supervised Classification:
  - Feed-forward multi-layer perceptrons with back propagation,
  - Radial Basis Functions,
  - Learning Vector Quantization.

Artificial Neural Networks

- **Classifiers;**
  - Multi-Layer Perceptrons,Self Organizing Maps, Learning Vector Quantization
- **Interpolators:**
  - Probabilistic Neural Networks, Radial Basis Function Networks

Classifiers

- Based on the discriminating features, classifiers identify objects as belonging to different classes.

- **Supervised Networks**: Learn from user given examples. The learning rate is examined by blind testing

- **Unsupervised Networks**: Learn by [illegible]ing organization within the dataset [illegible]

Interpolators:

- They learn as supervised networks by training on given data sets,
- They are similar to multi-channel Wiener prediction filters, except, prediction could be non-linear,
- Continuously varying physical parameters may be predicted, such as porosity, shale percent, water saturation and etc.

Calibration

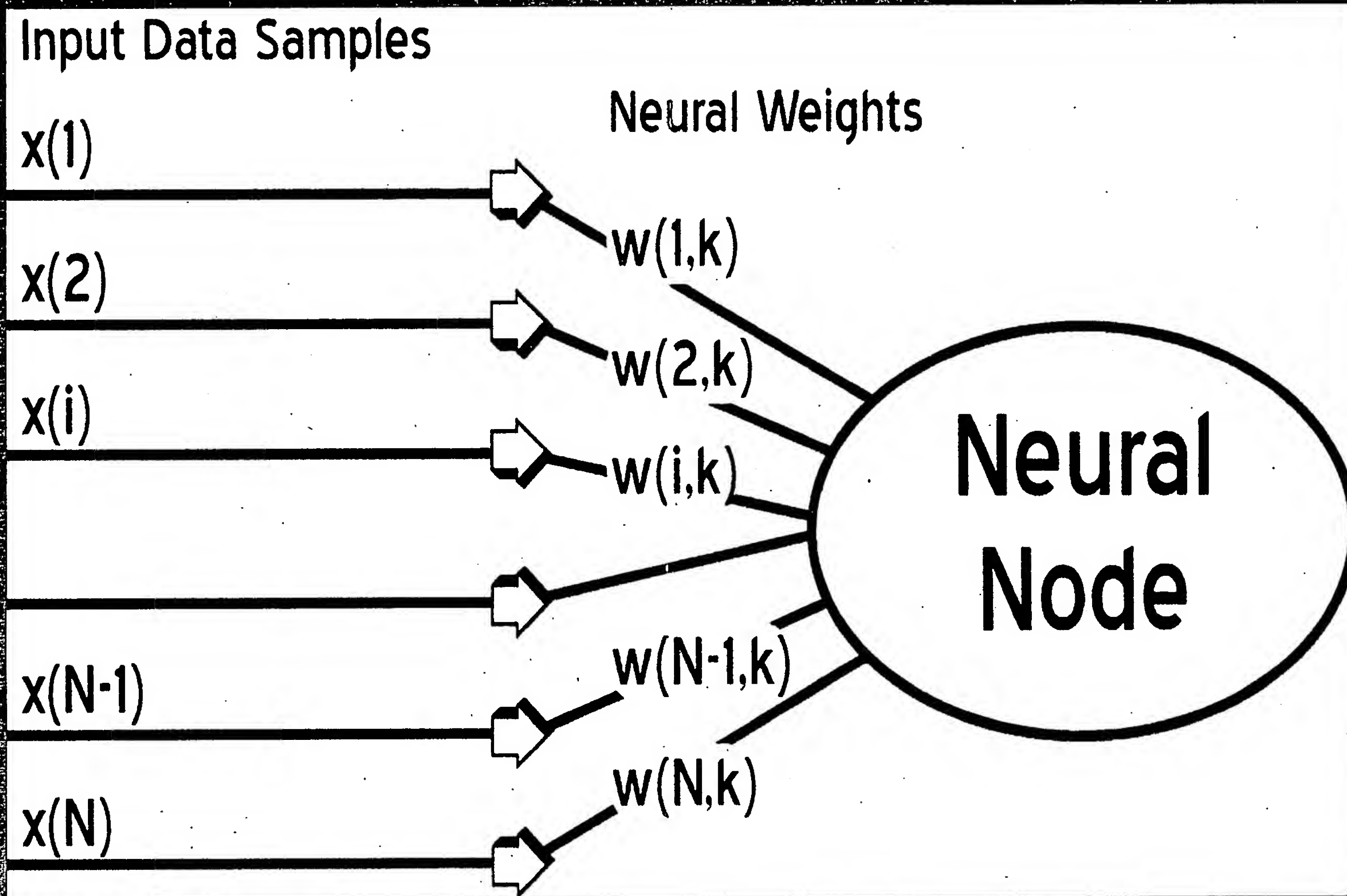
- Calibration establishes a direct relation between classes and physical, lithologic and reservoir related measurements.
- Unsupervised classification has to follow a calibration session.
- Supervised trained networks classification is calibrated during the training.

Kohonen's Self Organizing Feature Maps

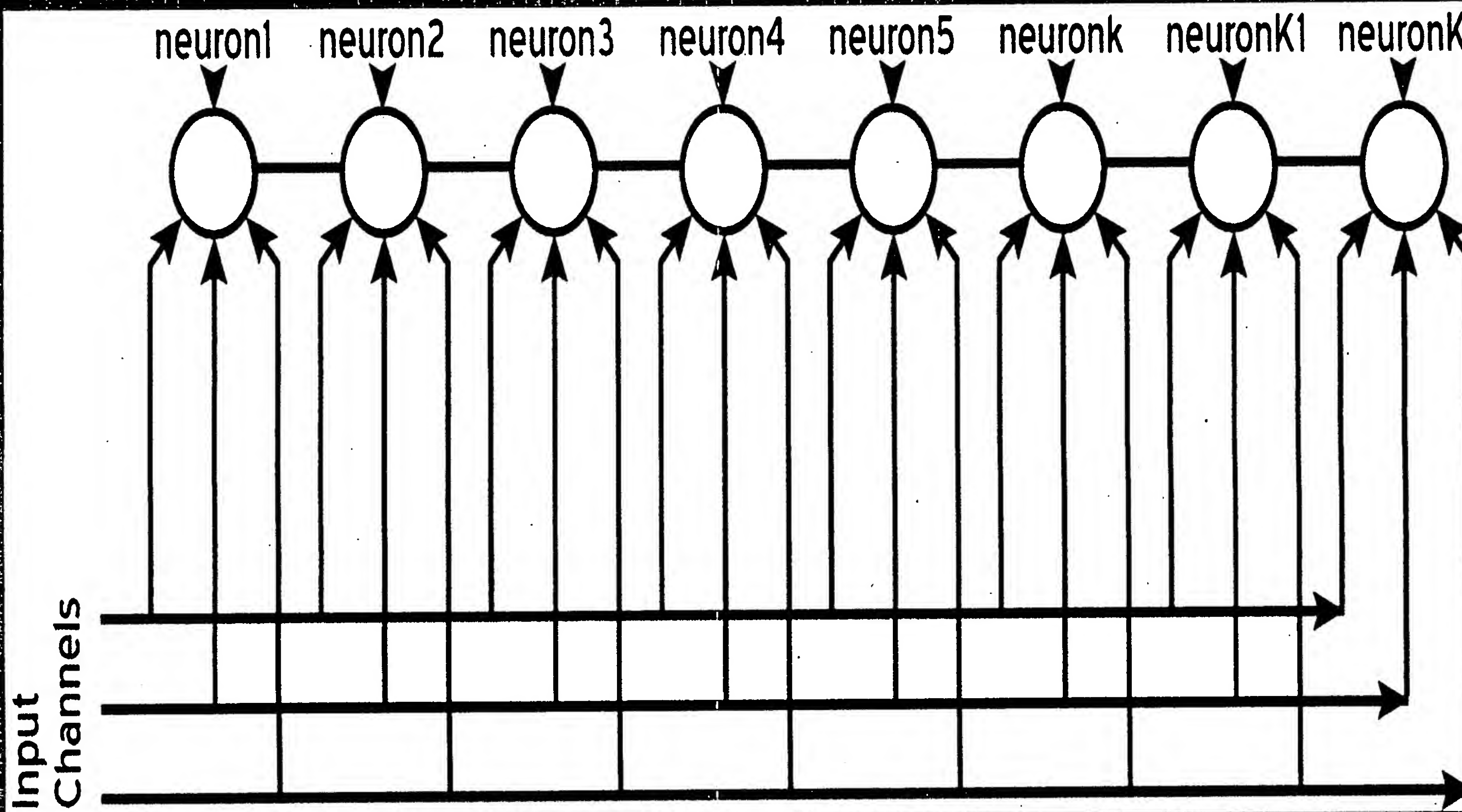
- Is an unsupervised clustering method,
- Clusters are organized in the data space according to user specification,
- Neural weights define the cluster centers in the input data space
- It is in the form of one layer feed forward network
- It uses "Winner take all" logic with neighborhood consideration
- Clustering is based on the input data structure, does not have direct relation to reservoir characteristics

Input Data

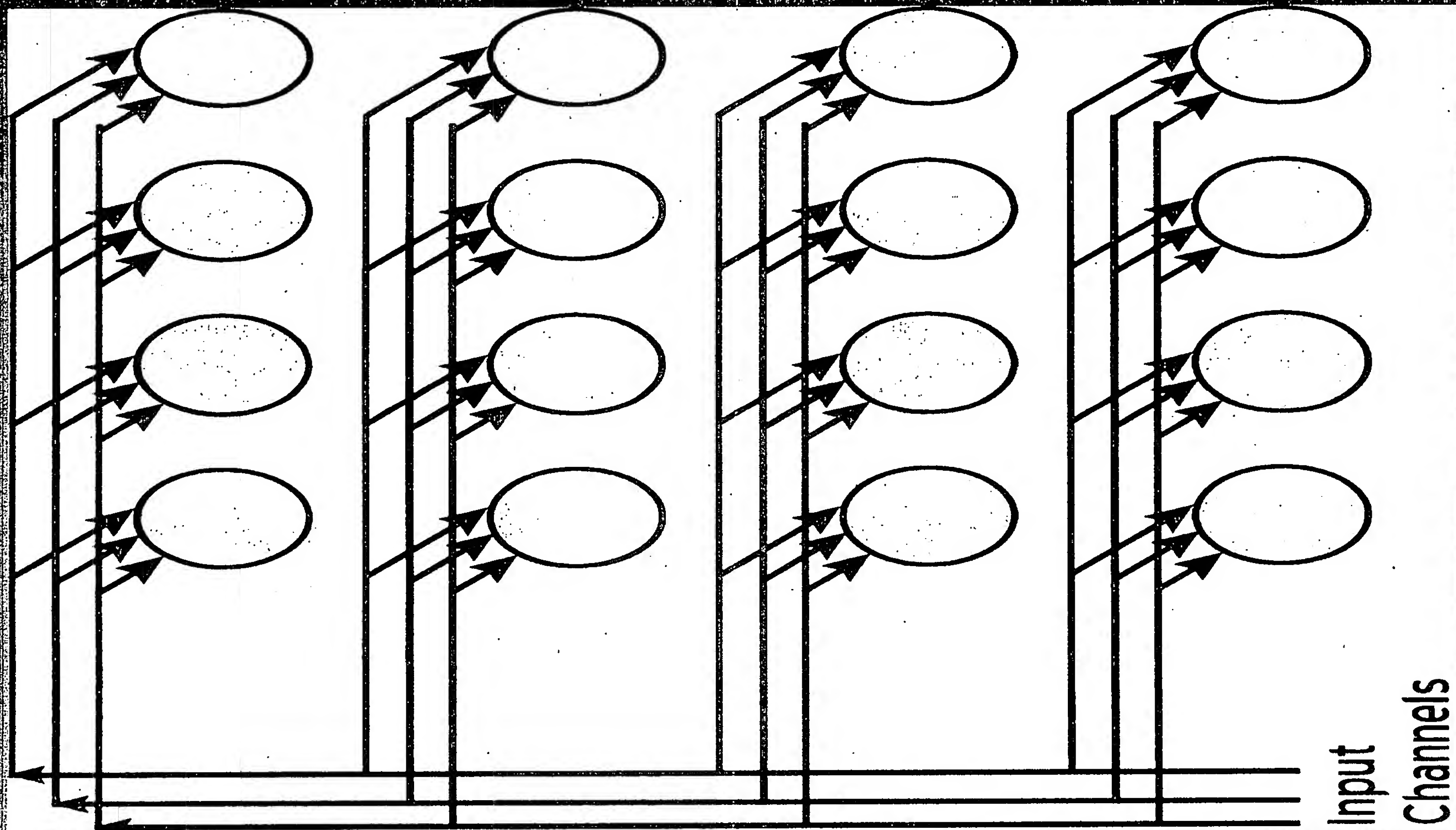
- Input data may be single data sample or a portion of seismic data trace
- In the single data sample case, many combinations of attributes may be used
- Clustering will reflect the character of input attributes
- Input data is considered as a vector in N dimensional space
- AVO, instantaneous, wavelet, geometrical attributes or their Eigen projections may be used



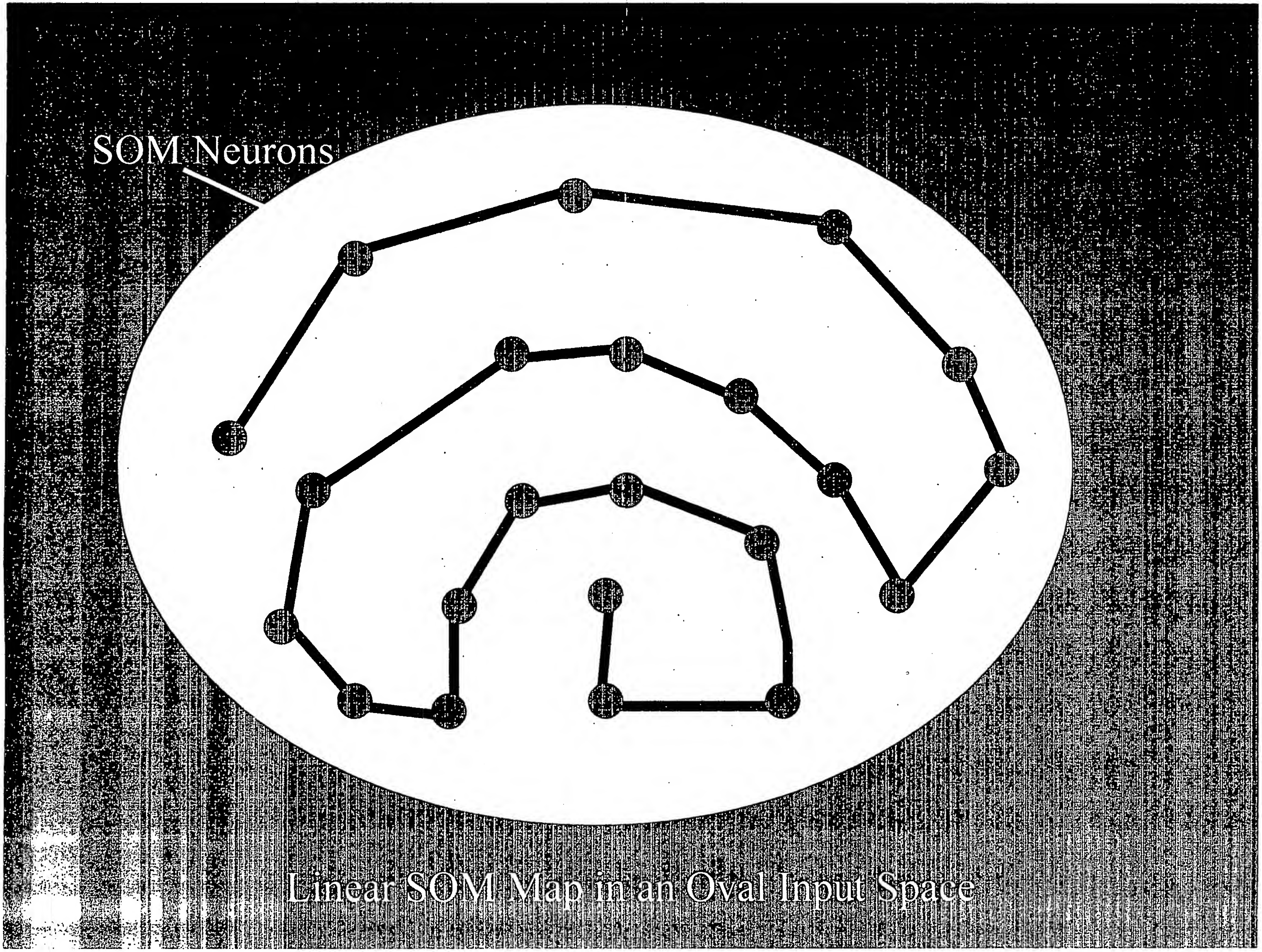
A Neural Node of SOM

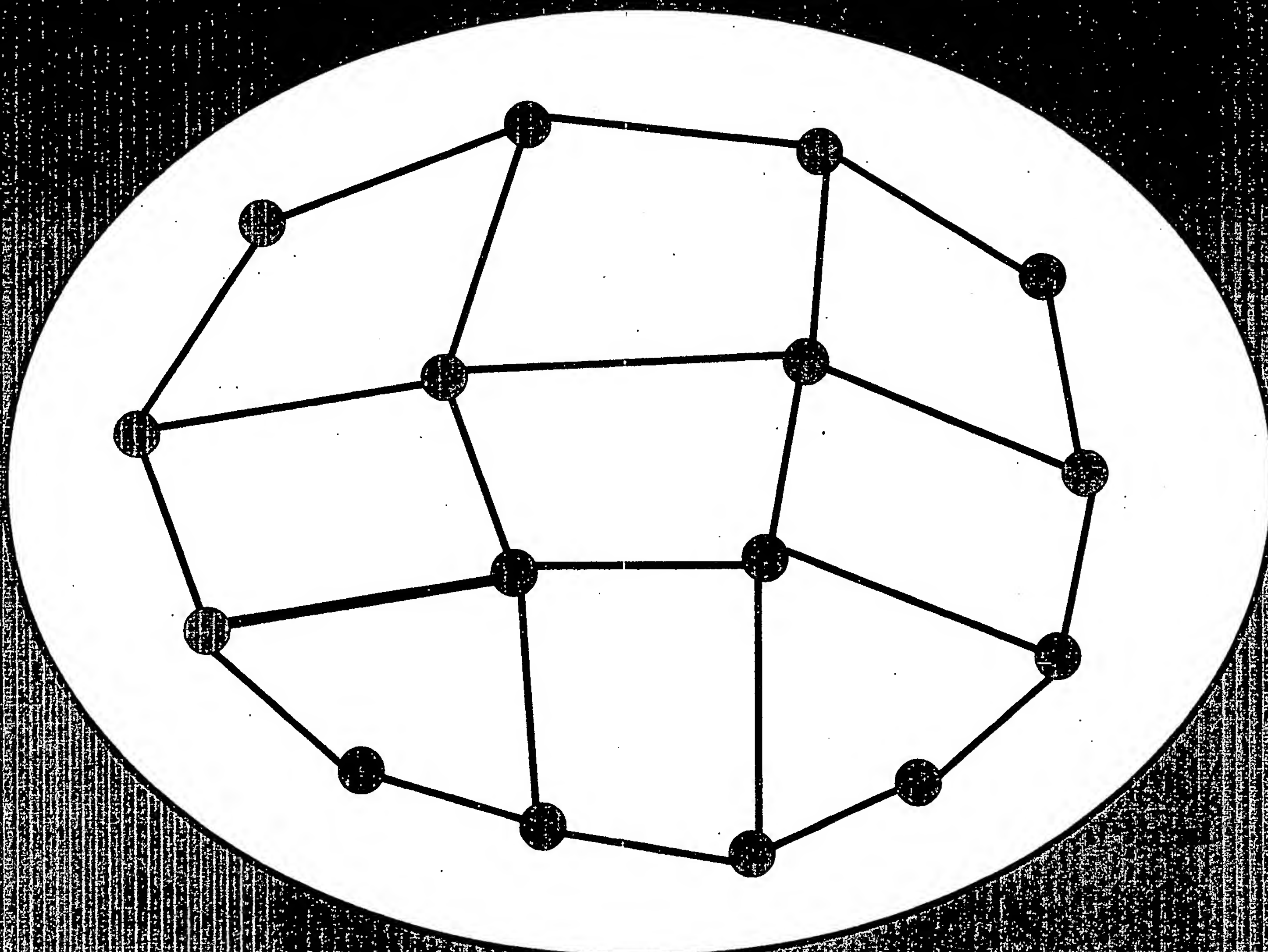


A Linear Neuron Setting of SOM

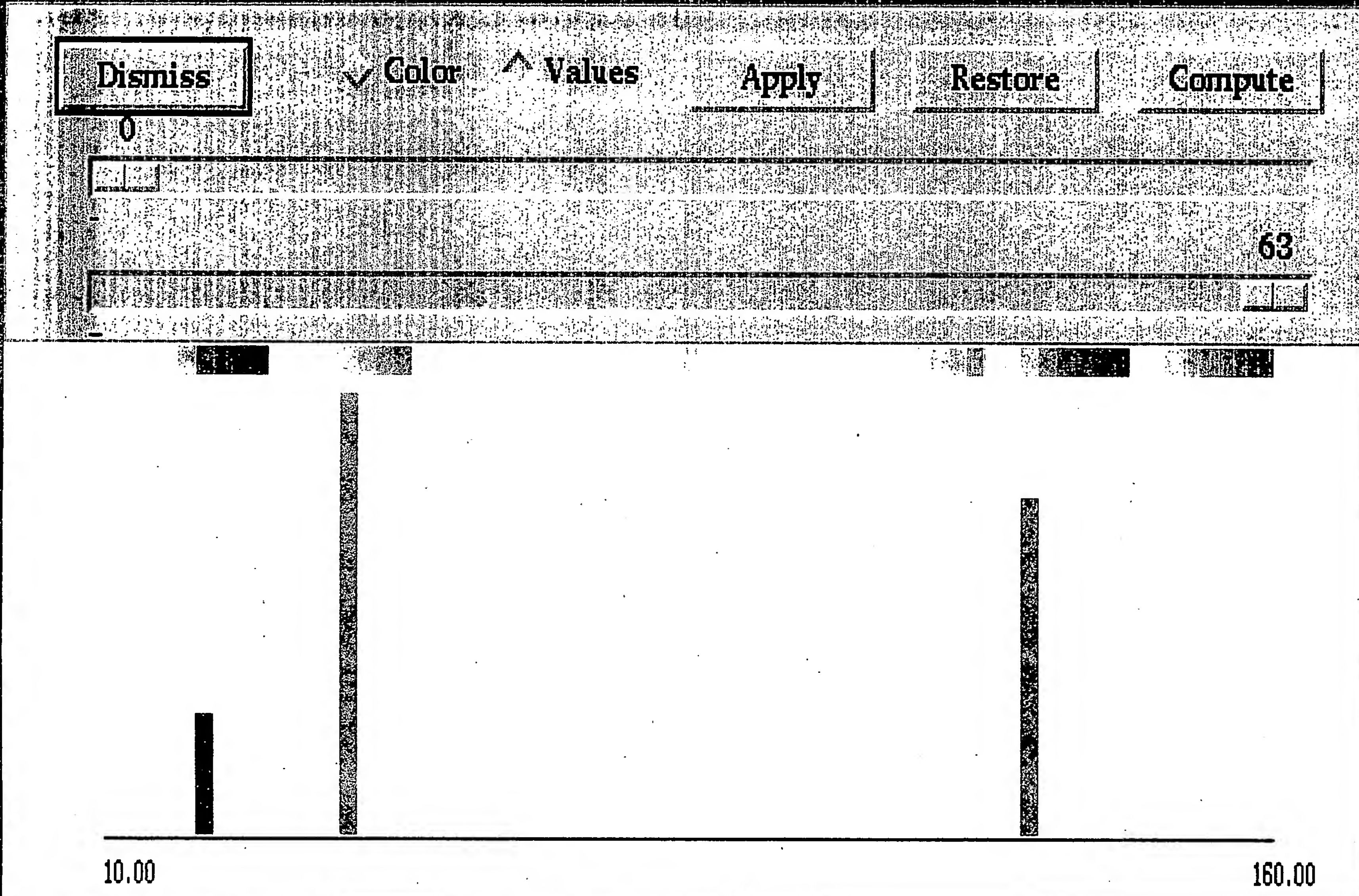


A (2-D) Rectangular Setting of SOM

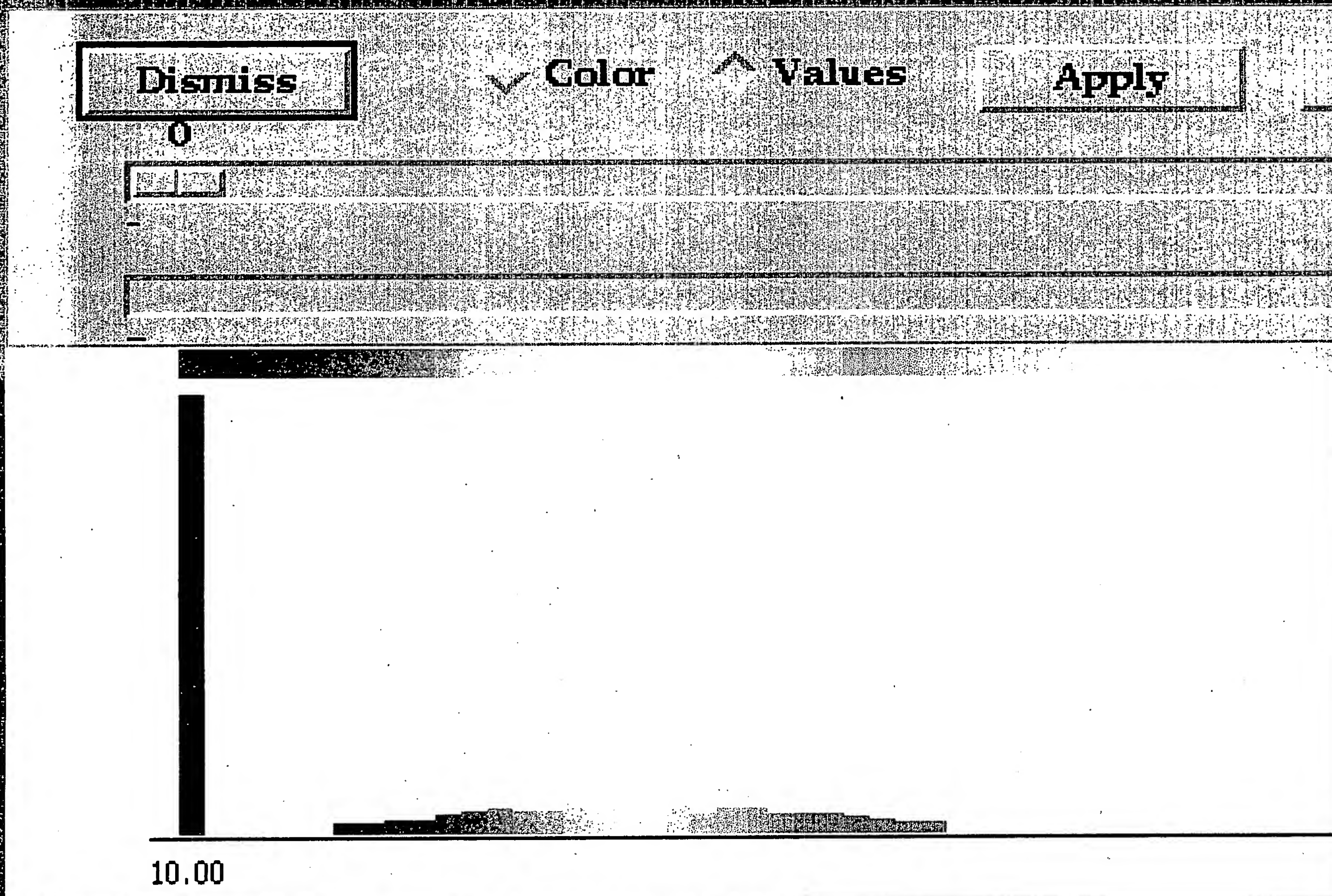

SOM Neurons
Linear SOM Map in an Oval Input Space



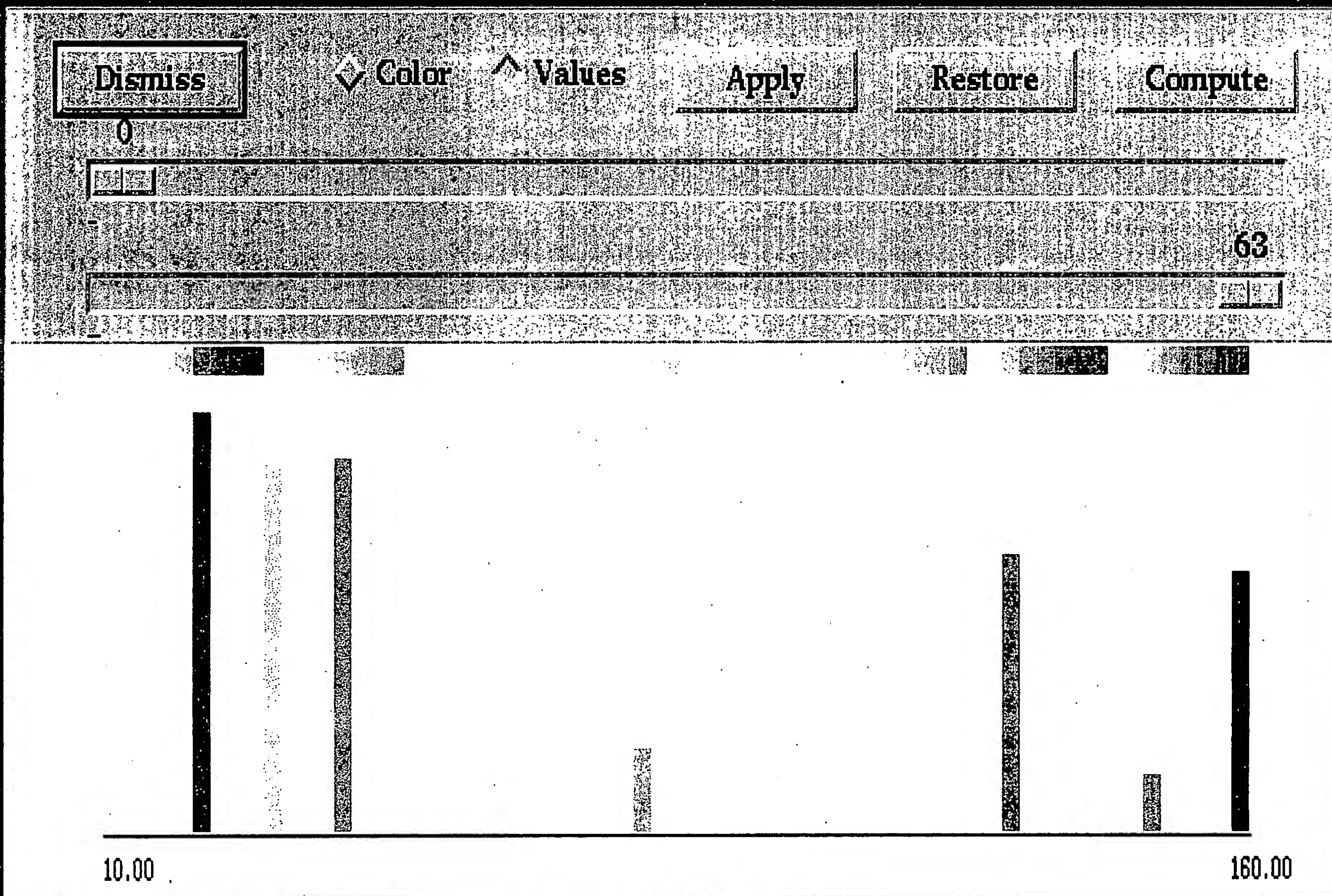
Rectangular SOM Map in an Oval Input Space



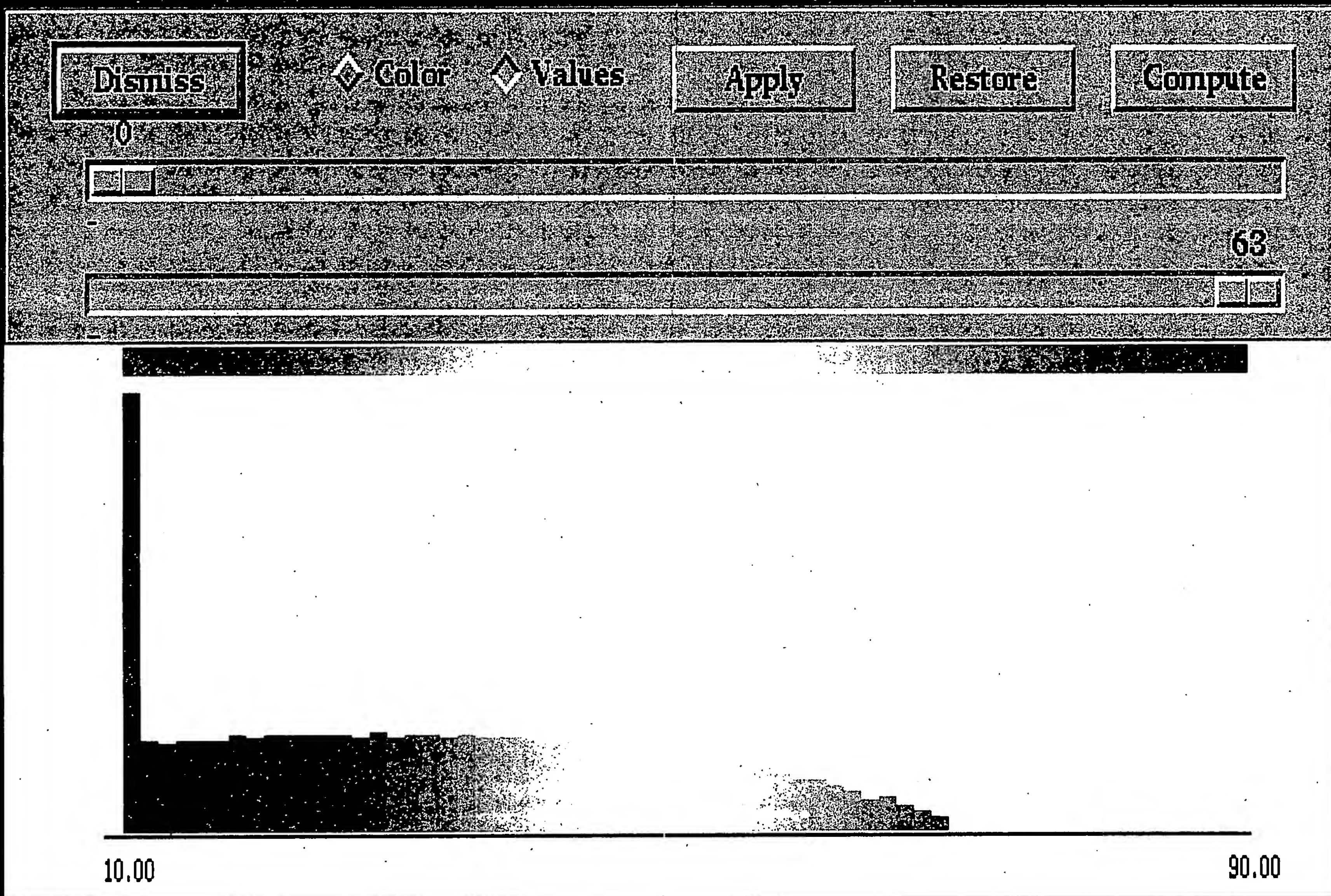
Classification Population Histogram after 2 Passes



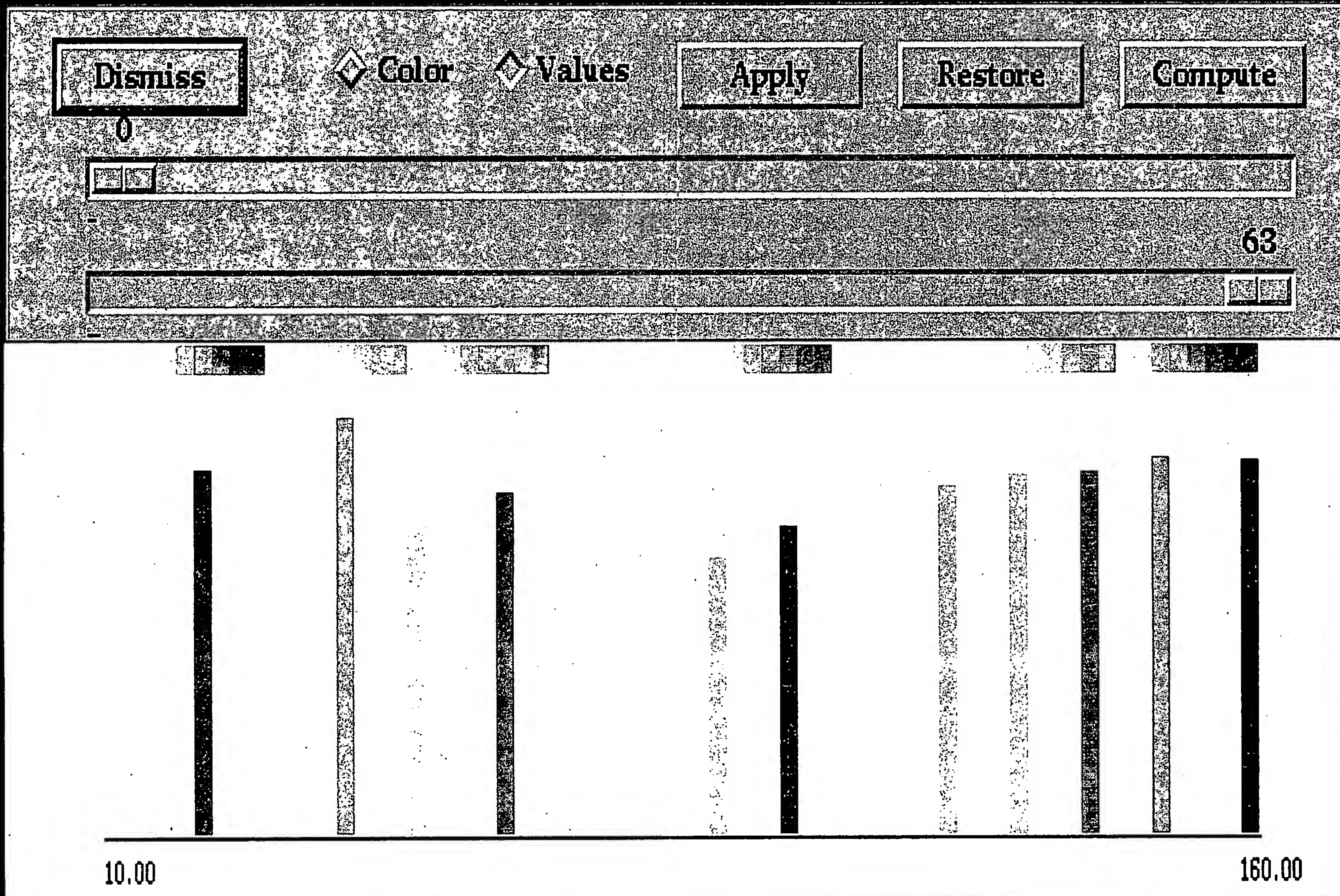
Confidence Level Histogram after 5 Passes



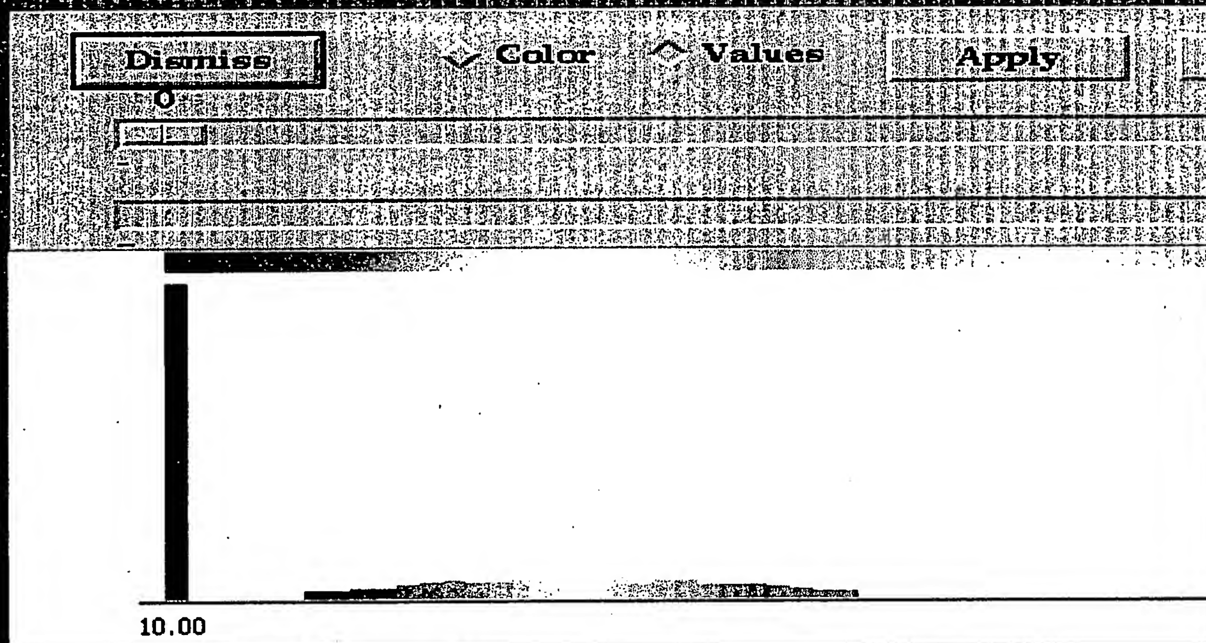
Classification Population Histogram after 36 passes



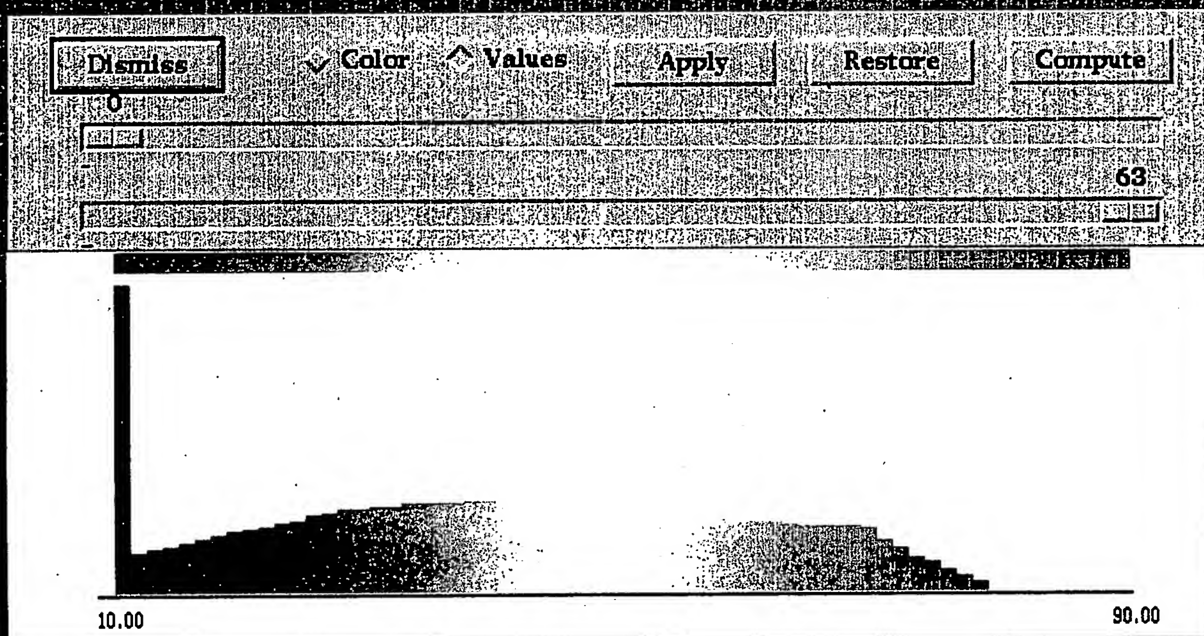
Confidence Level Histogram after 36 Passes



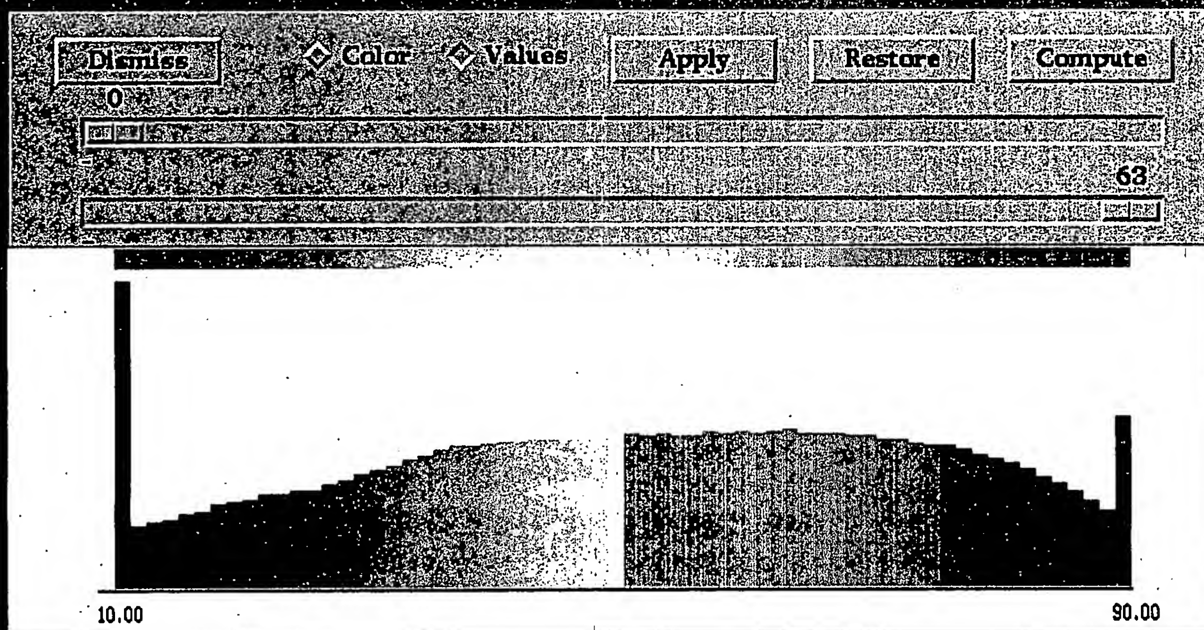
Classification Population Histogram after 94 Passes



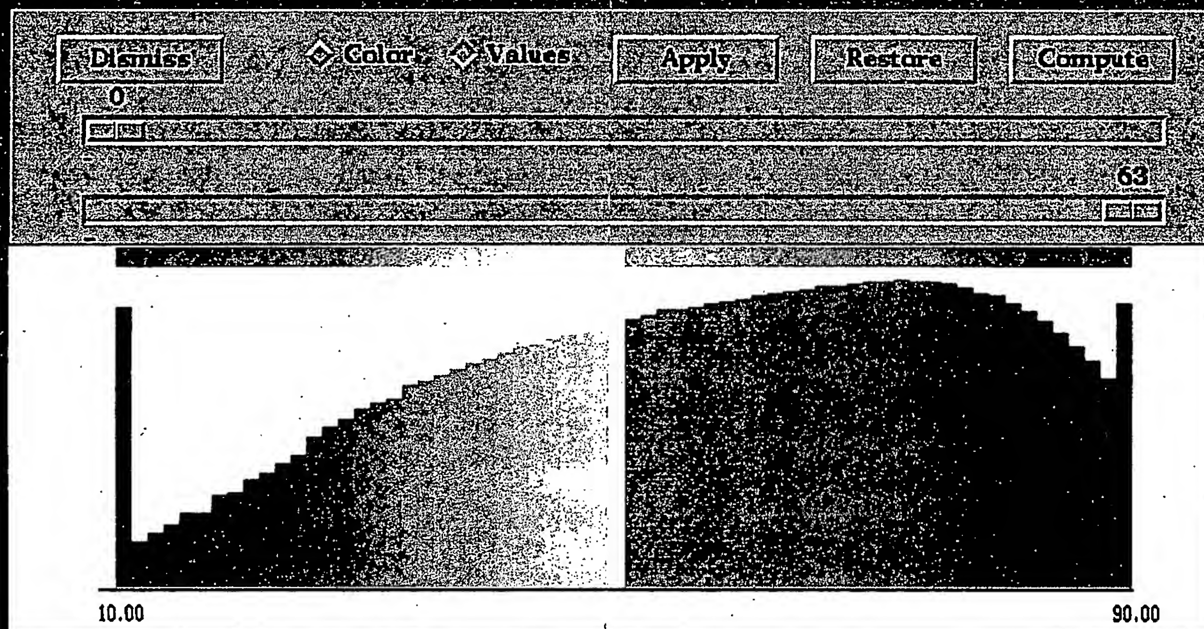
Confidence Level Histogram after 5 Passes



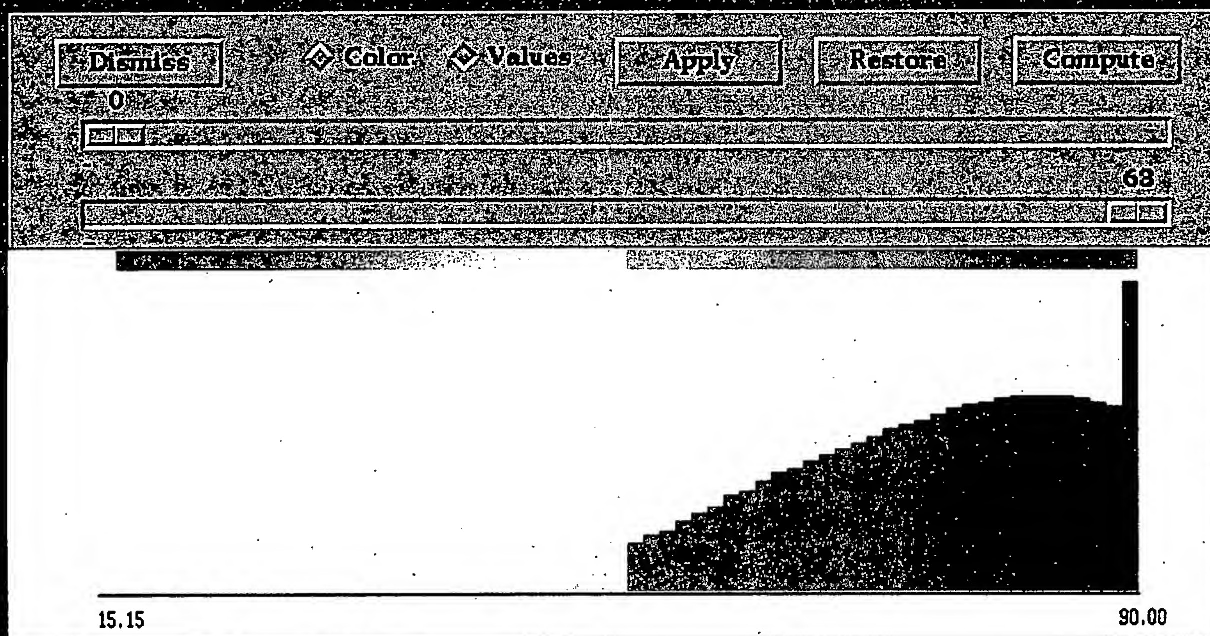
After 36 Passes



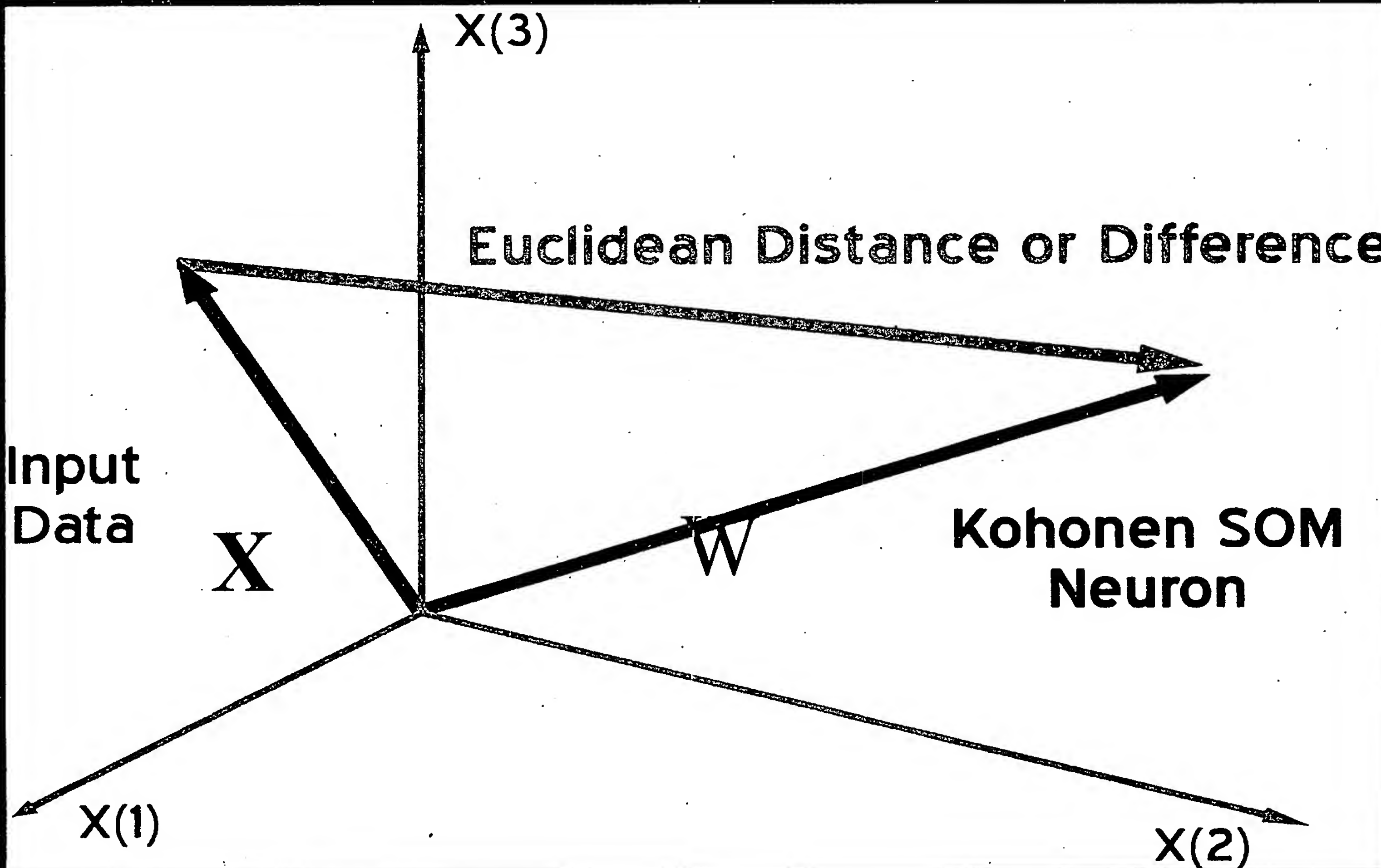
44 Passes



94 Passes

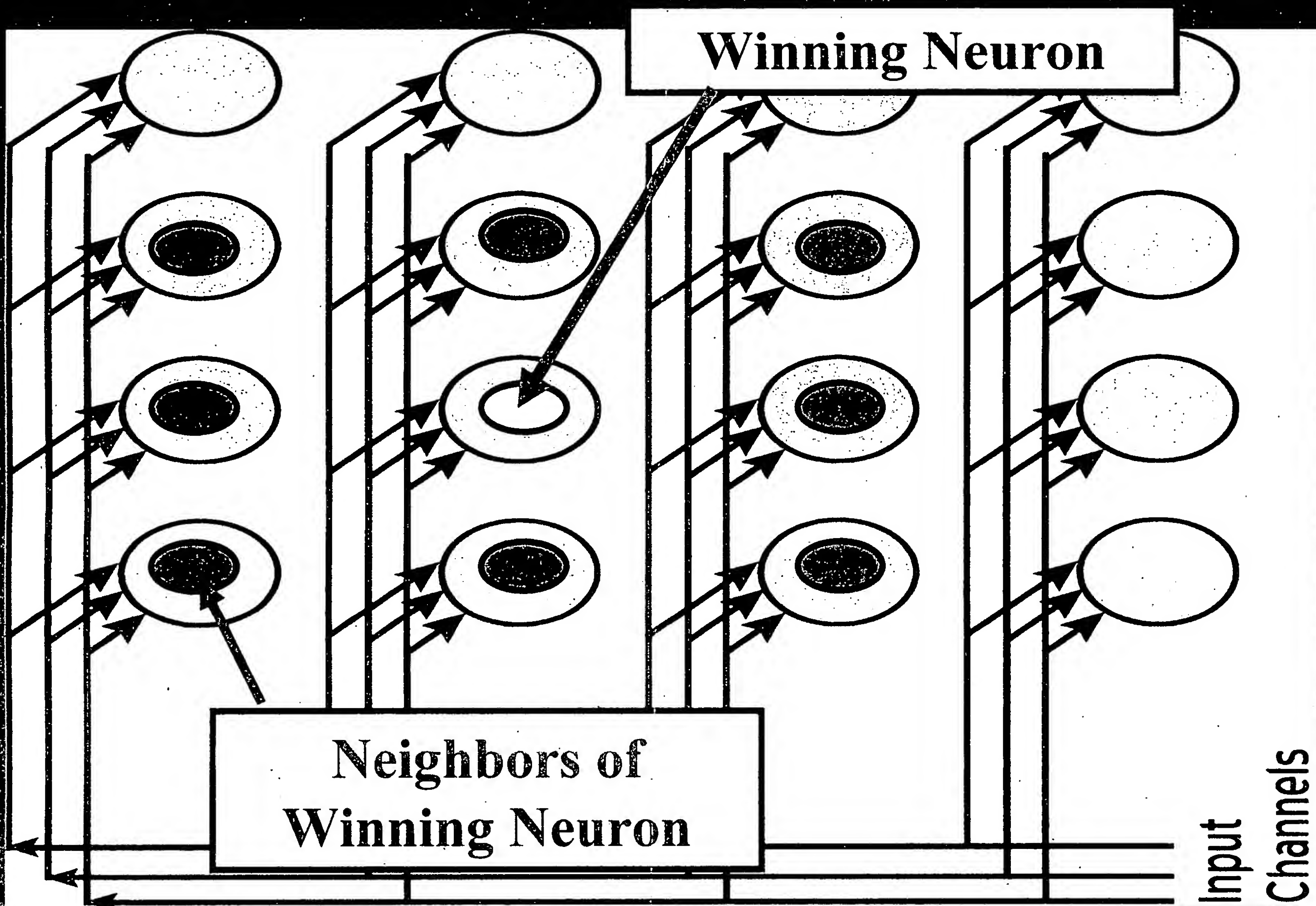


1300 Passes

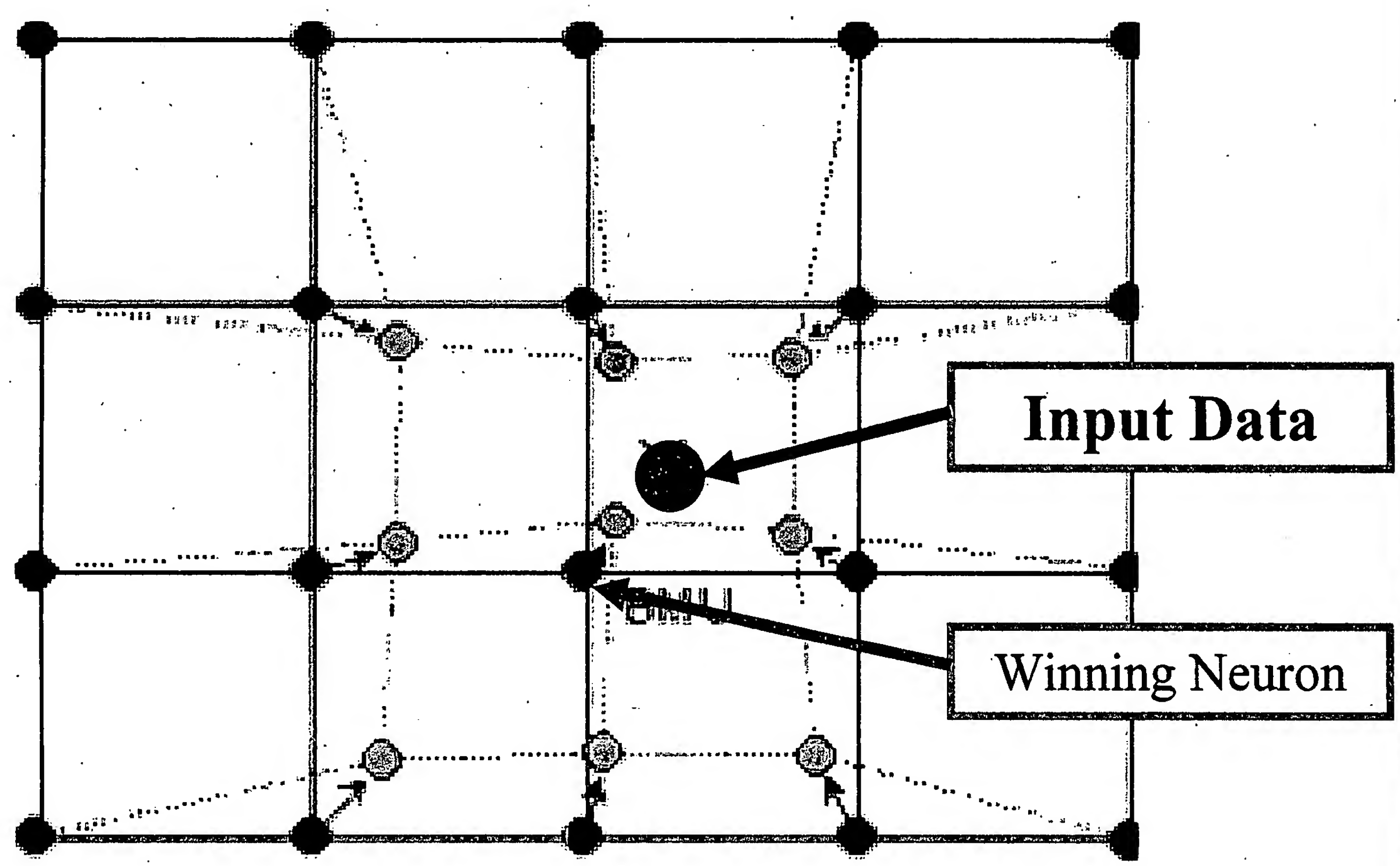


$$net_k = \sqrt{\sum_{i=1}^{N} [\, x(i) - w(i,k) \,]^2}$$

Euclidean Distance

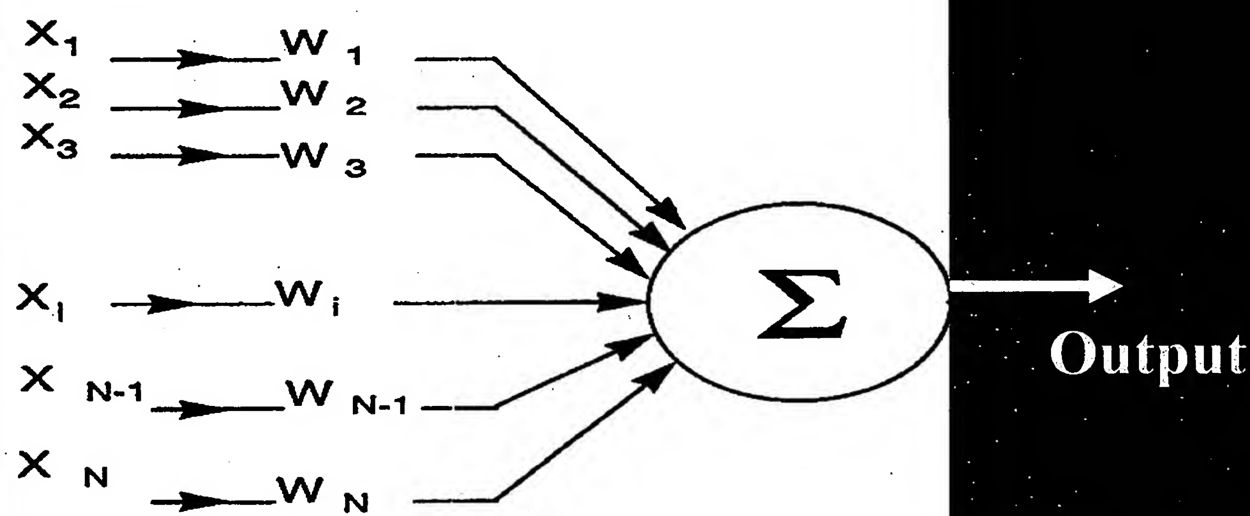


2-D Neighborhood Map of SOM

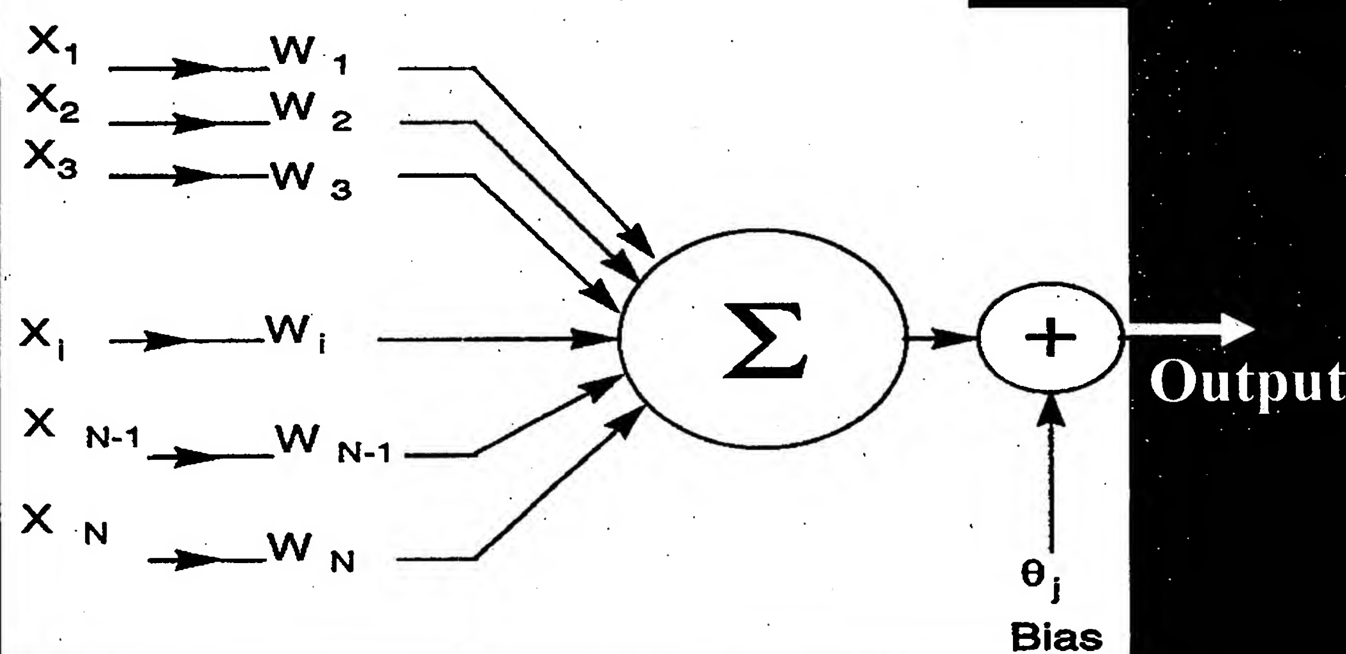


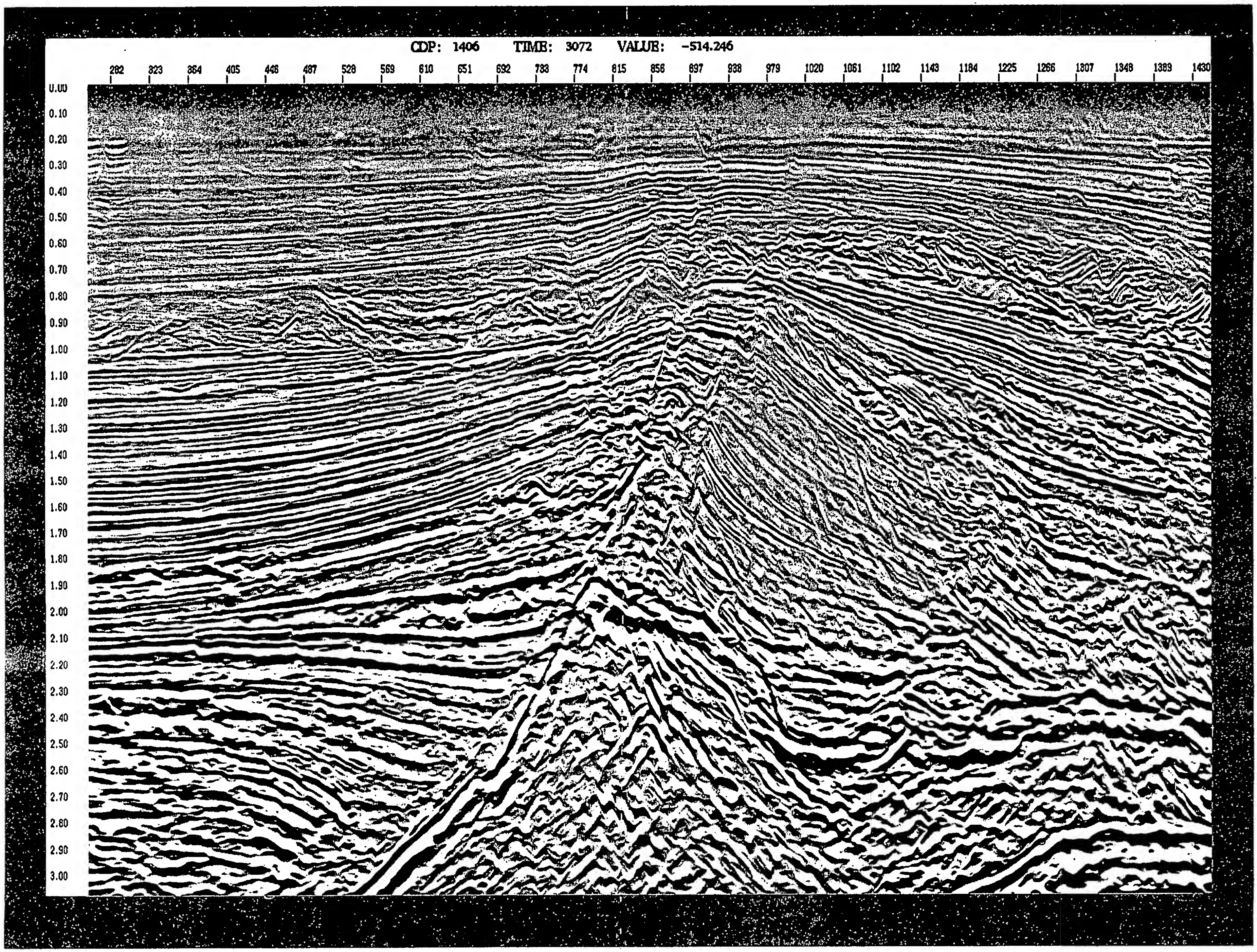
Neural Corrections at each Iteration

Original Configuration

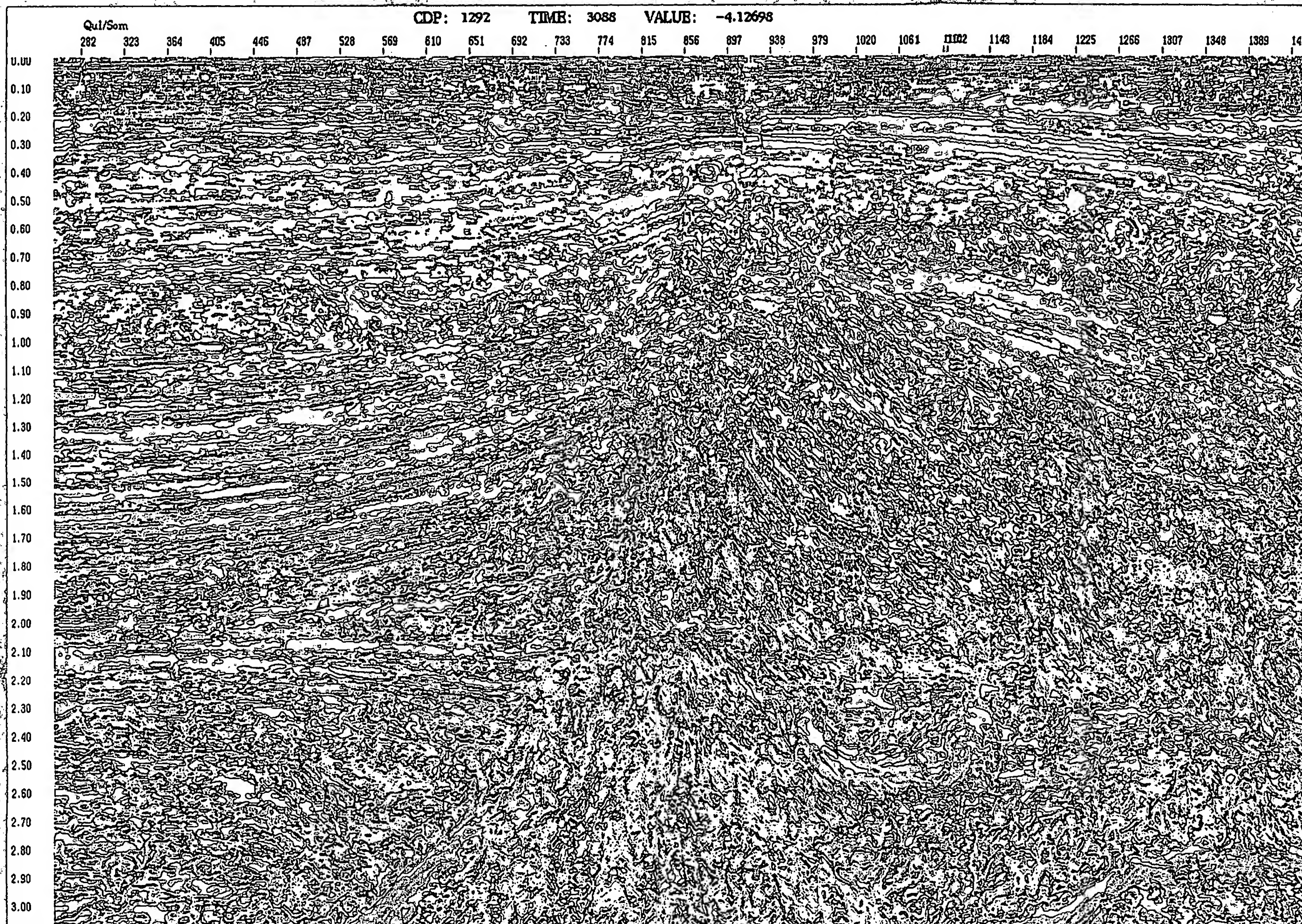


With Conscience

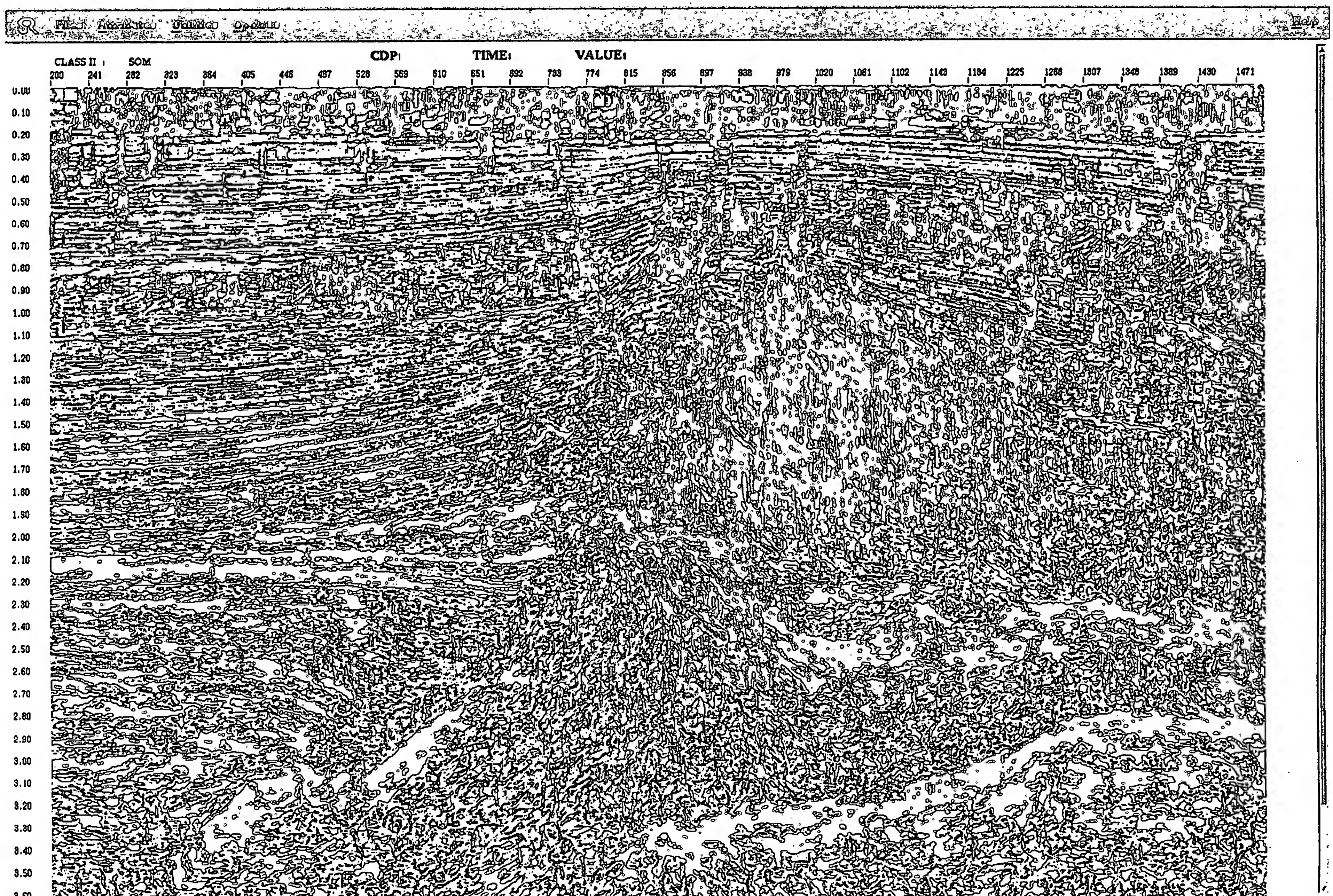




CDP: 1406 TIME: 3072 VALUE: -514.246
282 323 364 405 446 487 528 569 610 651 692 733 774 815 856 897 938 979 1020 1061 1102 1143 1184 1225 1266 1307 1348 1389 1430
0.00 0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80 0.90 1.00 1.10 1.20 1.30 1.40 1.50 1.60 1.70 1.80 1.90 2.00 2.10 2.20 2.30 2.40 2.50 2.60 2.70 2.80 2.90 3.00



Rock Solid Images


CLASS II : SOM
CDP:
TIME:
VALUE:
200 241 282 323 364 405 446 487 528 569 610 651 692 733 774 815 856 897 938 979 1020 1061 1102 1143 1184 1225 1266 1307 1348 1389 1430 1471
0.00 0.10 0.20 0.30 0.40 0.50 0.60 0.70 0.80 0.90 1.00 1.10 1.20 1.30 1.40 1.50 1.60 1.70 1.80 1.90 2.00 2.10 2.20 2.30 2.40 2.50 2.60 2.70 2.80 2.90 3.00 3.10 3.20 3.30 3.40 3.50 3.60

REFERENCES:

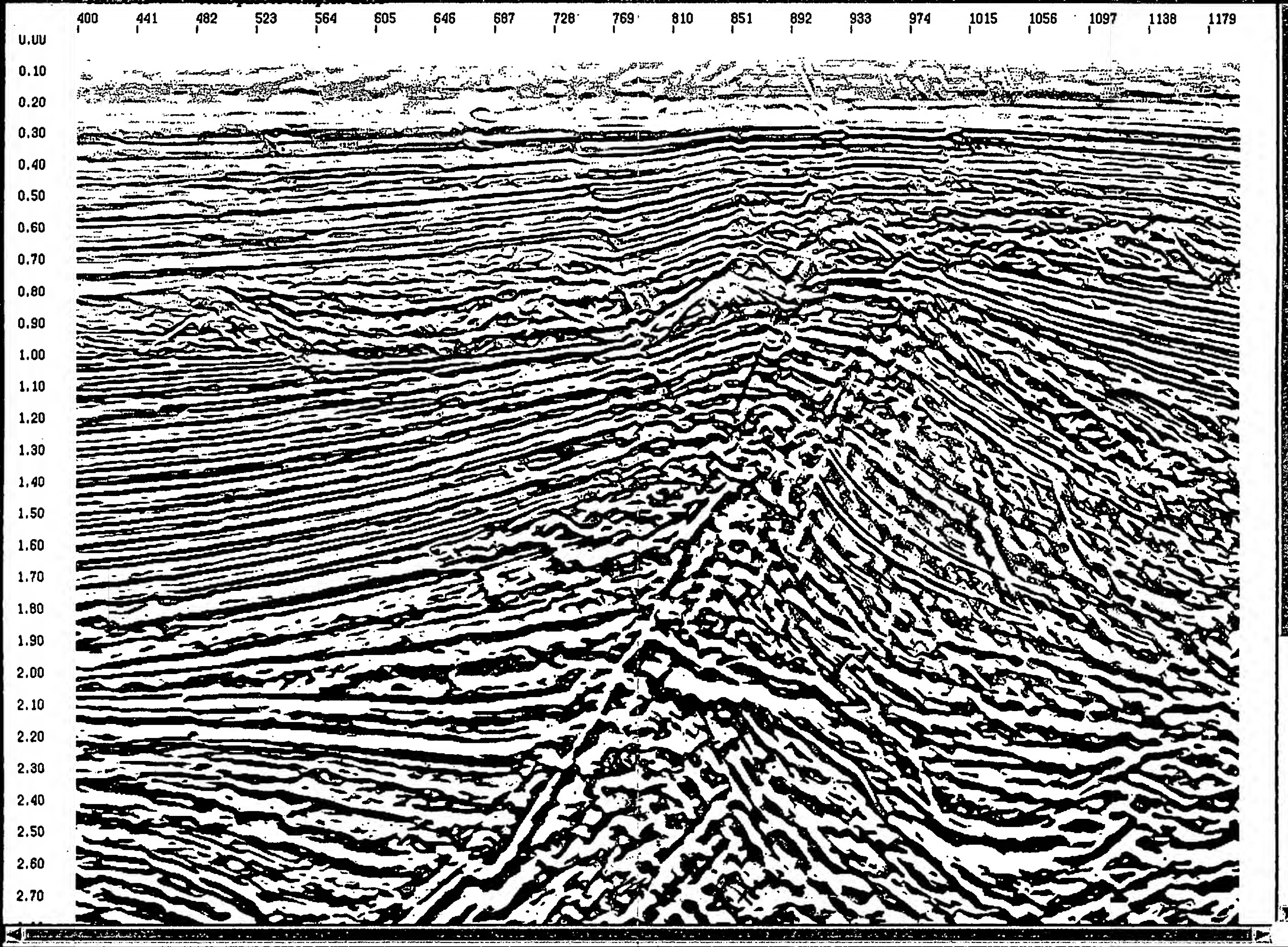
Proceedings of the IEEE , **1990**, Special issue on Neural Networks;
1. ***Neural Networks ,theory and modeling*** **(September** issue)
2.***Neural networks ,analysis, techniques and applications*** (**October** issue) (These issues have extensive literature and background articles)

Haykin, S. 1994, ***Neural Networks, A comprehensive foundation.*** Macmillan Publishing Company.

Bishop, C. M. 1999, ***Neural Networks for Pattern Recognition***. Oxford University Press.

Kohonen, T., 1997, ***Self Organizing Maps*, Springer series in Information Sciences, No. 30, pp203-217.**

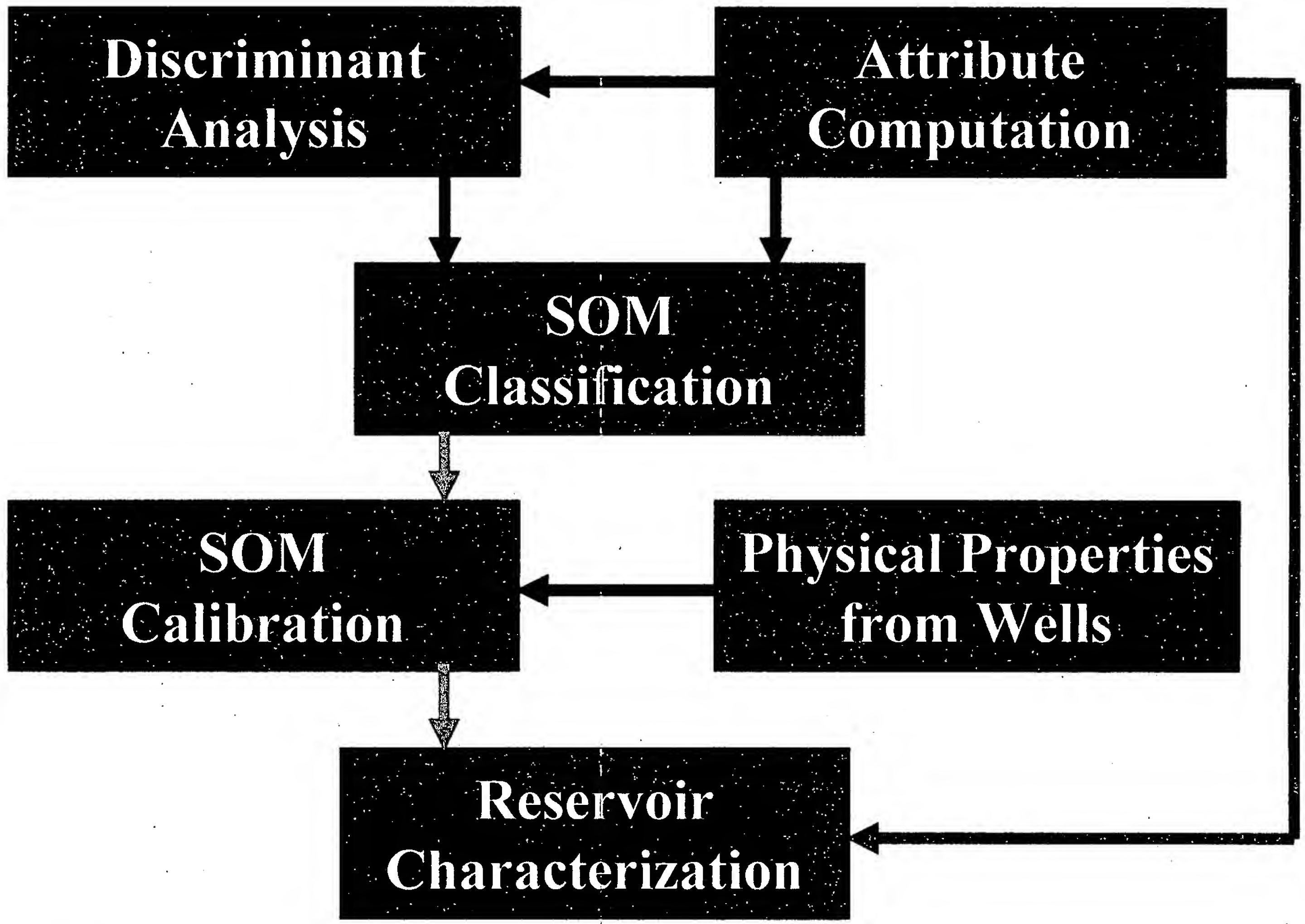
Rock Solid Images Web: ***www.rocksolidimages.com***



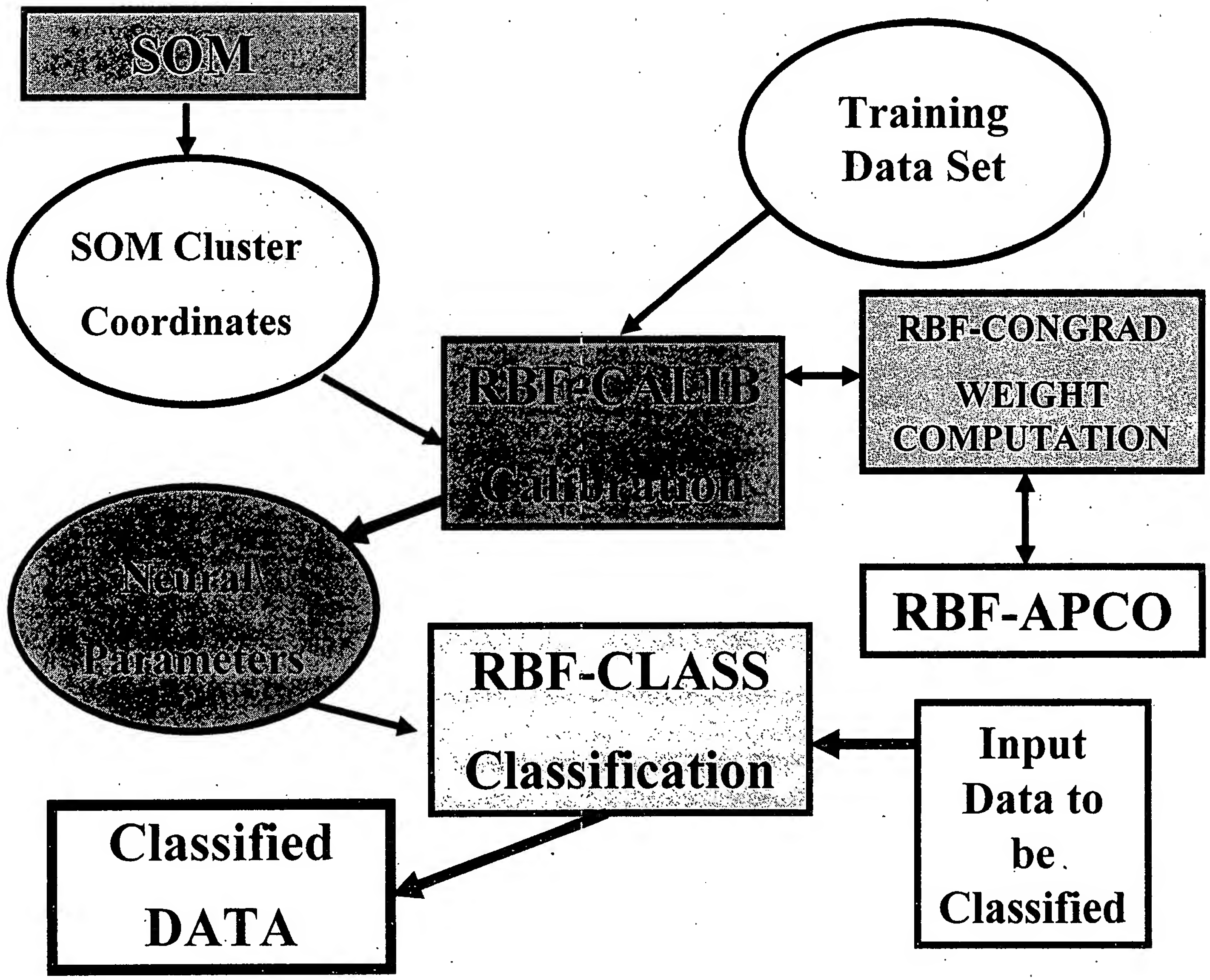
Rock Solid Images

Input section to SOM

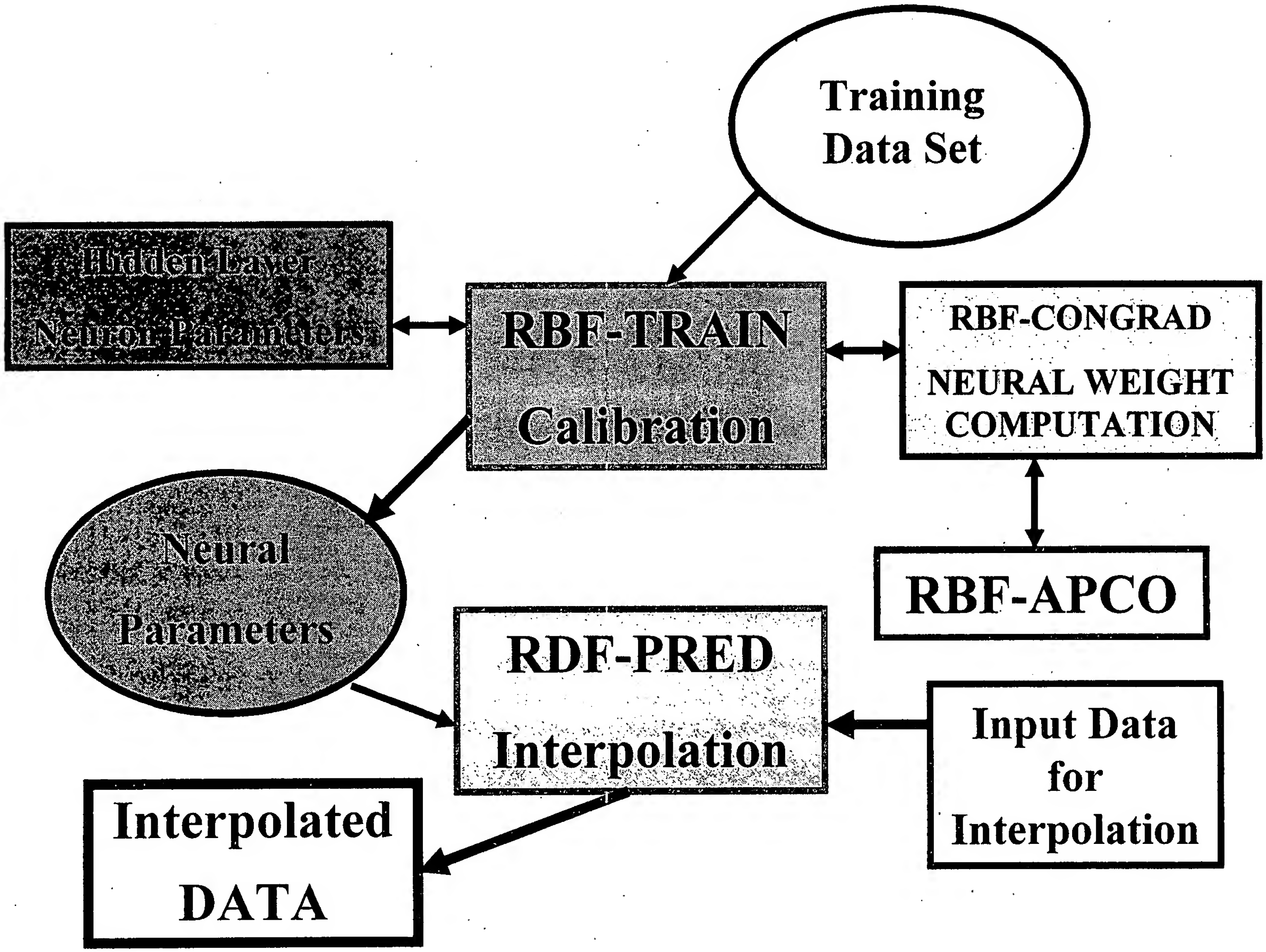
Low Confidence Level Display



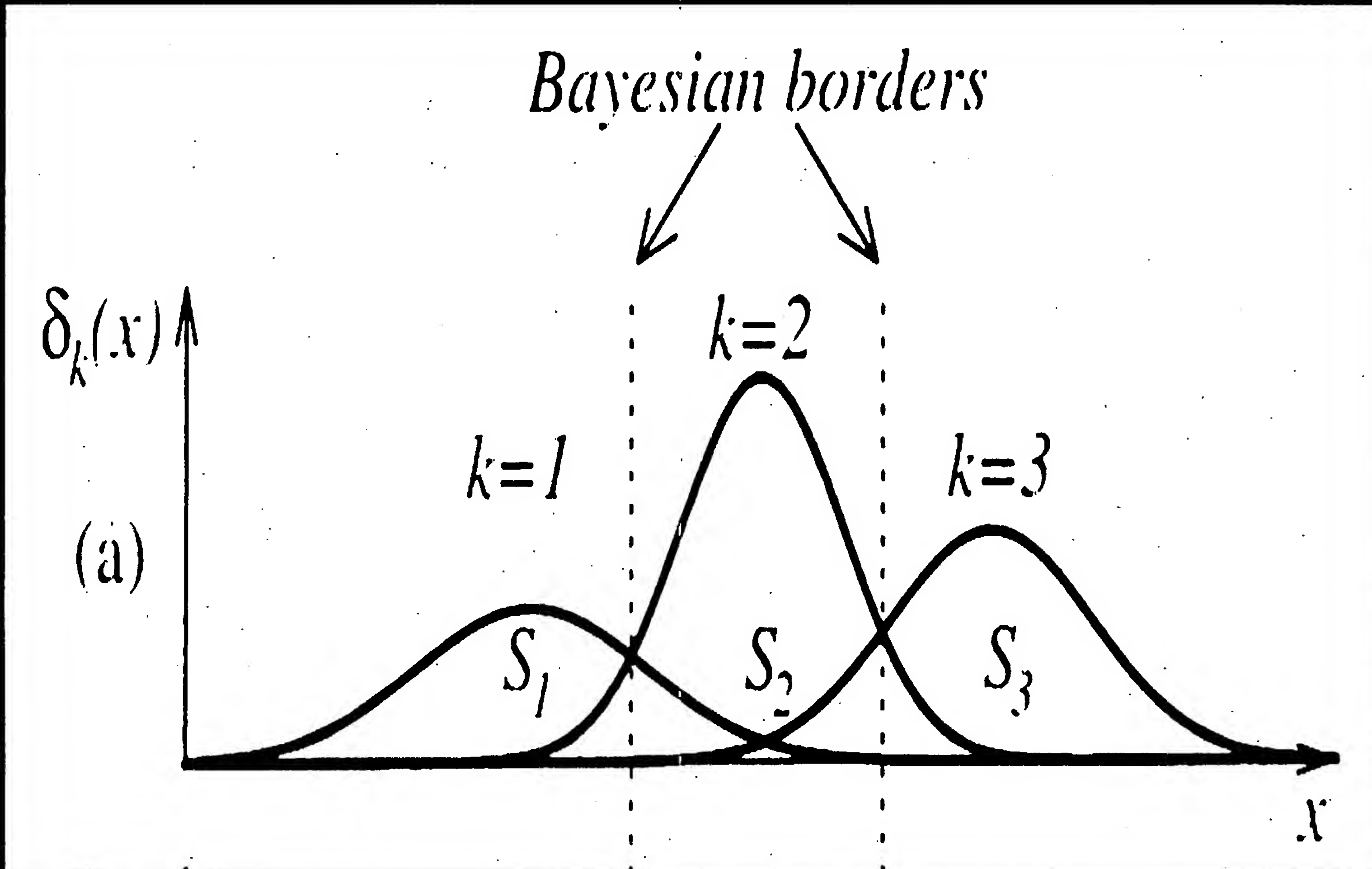
General Flow Chart of SOM Characterization



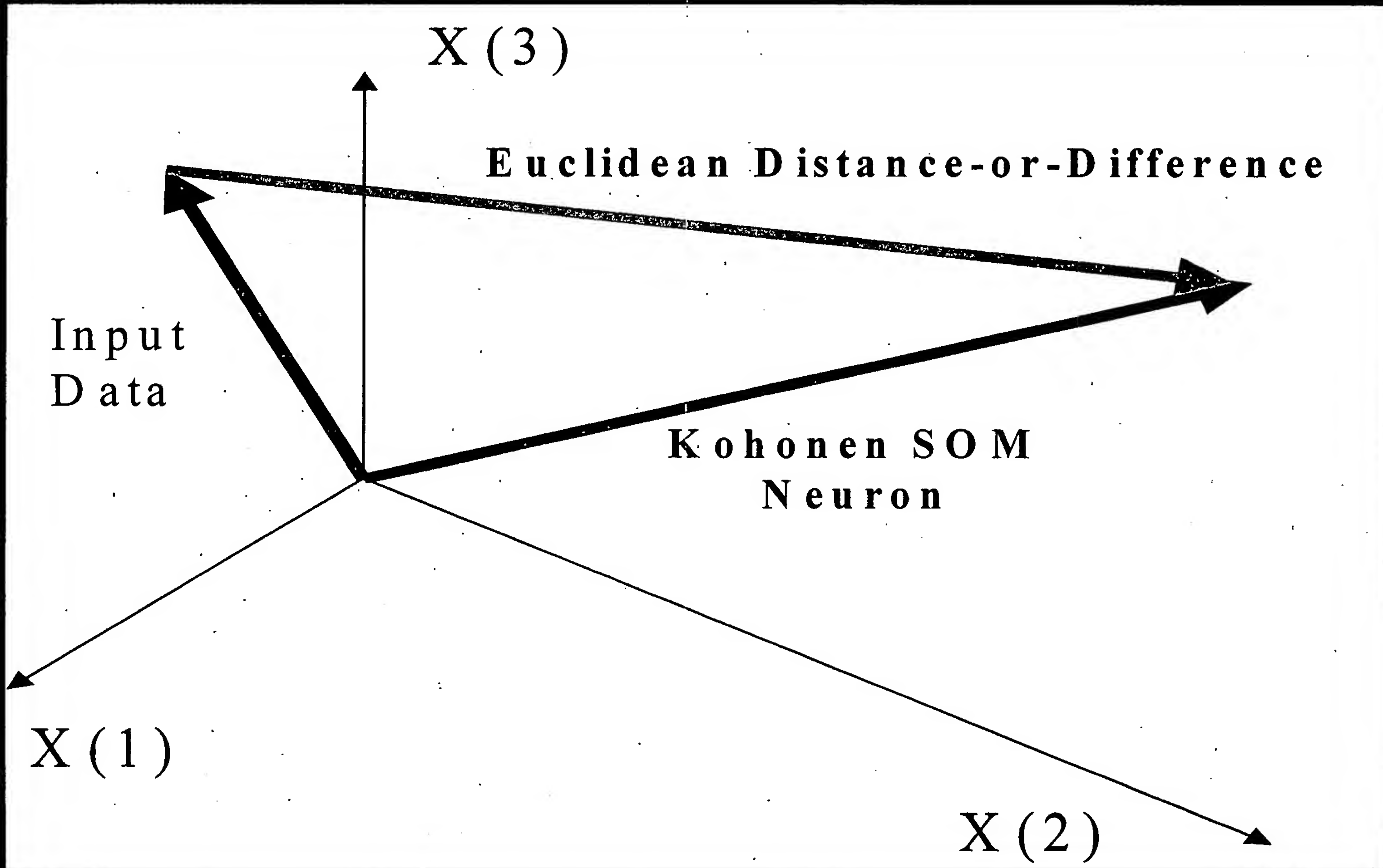
SOM Type RBF Training and Classification



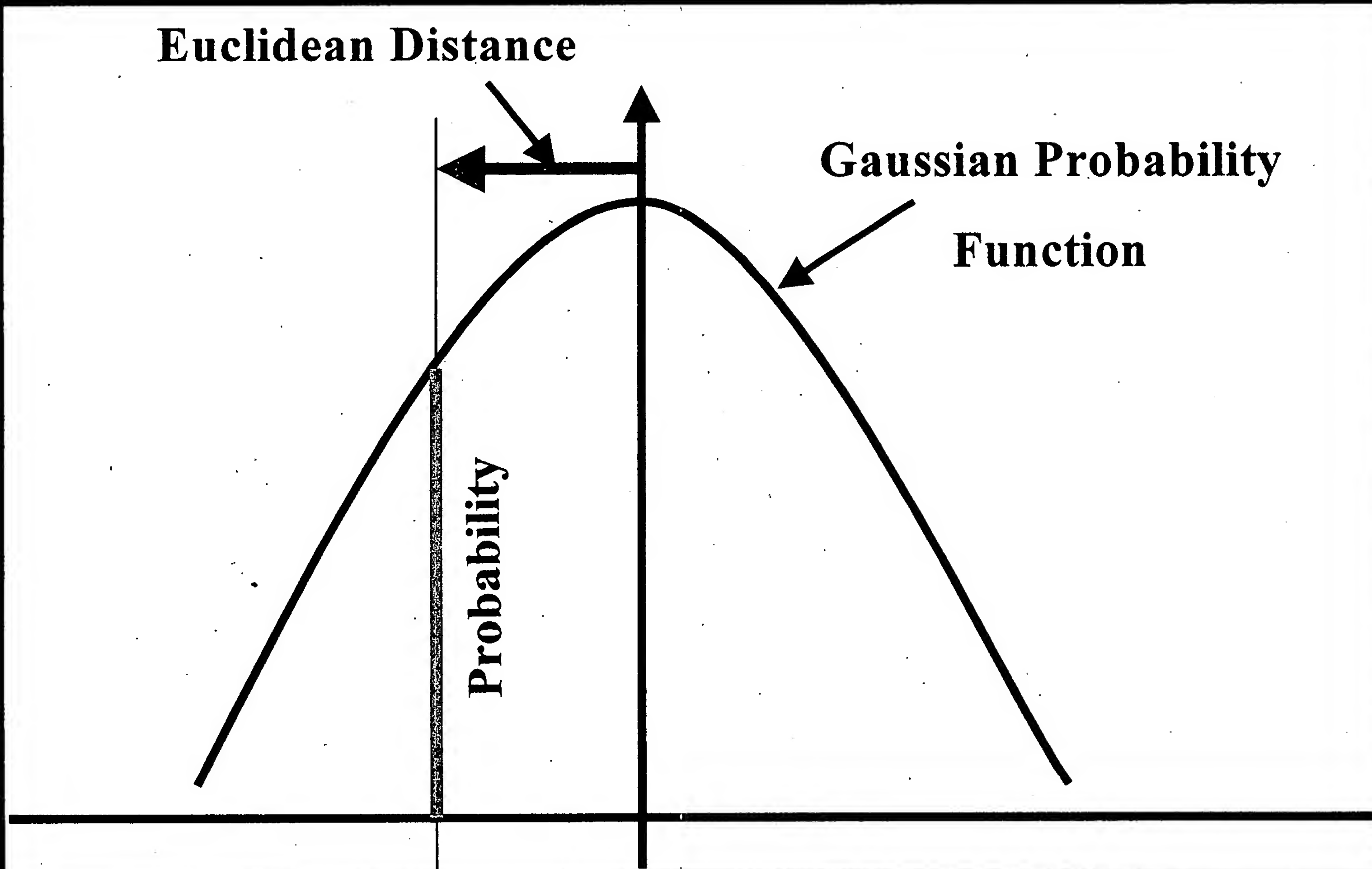
RBF Training and Interpolation/Prediction



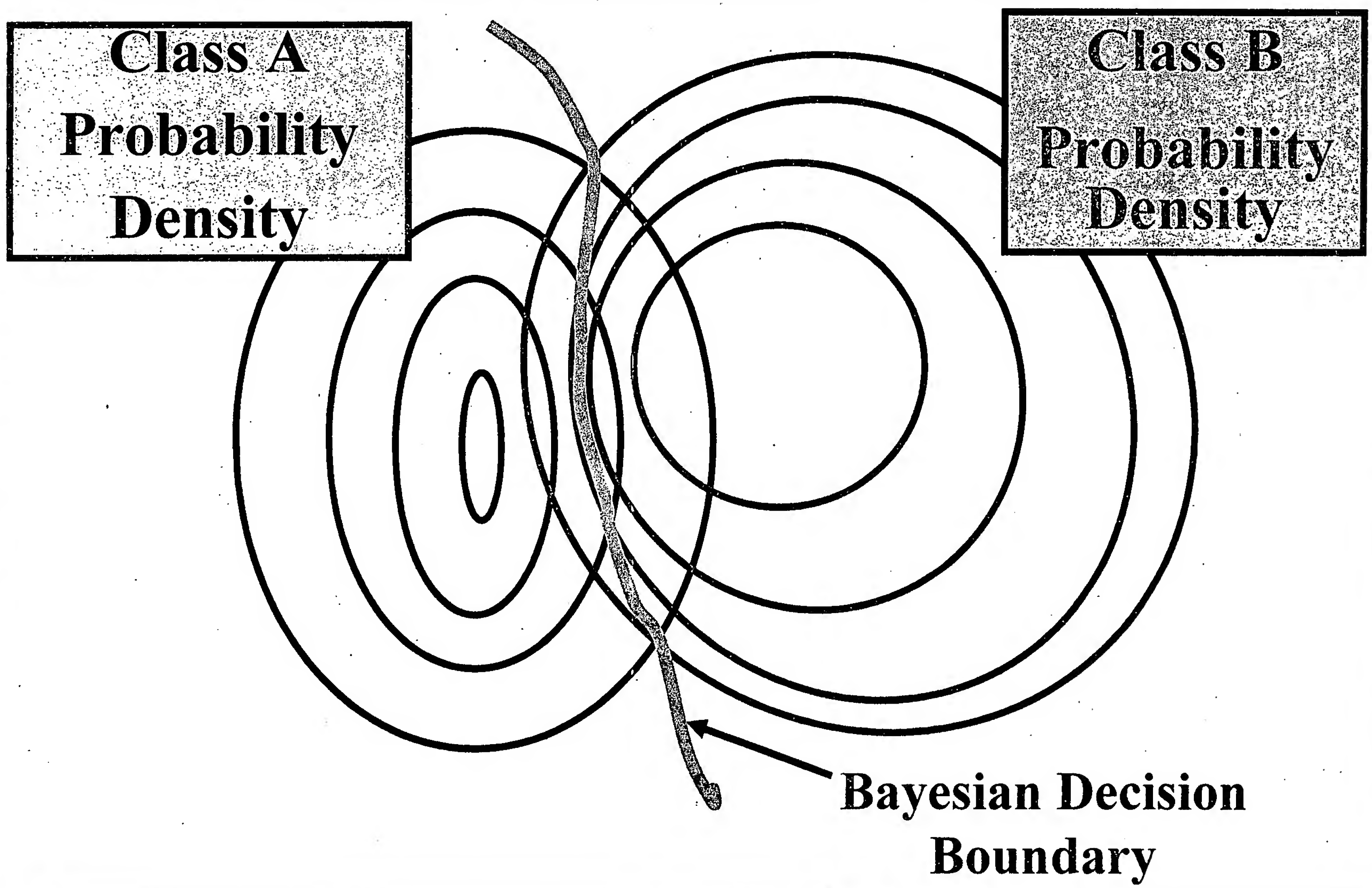
Bayesian Decision Boundaries

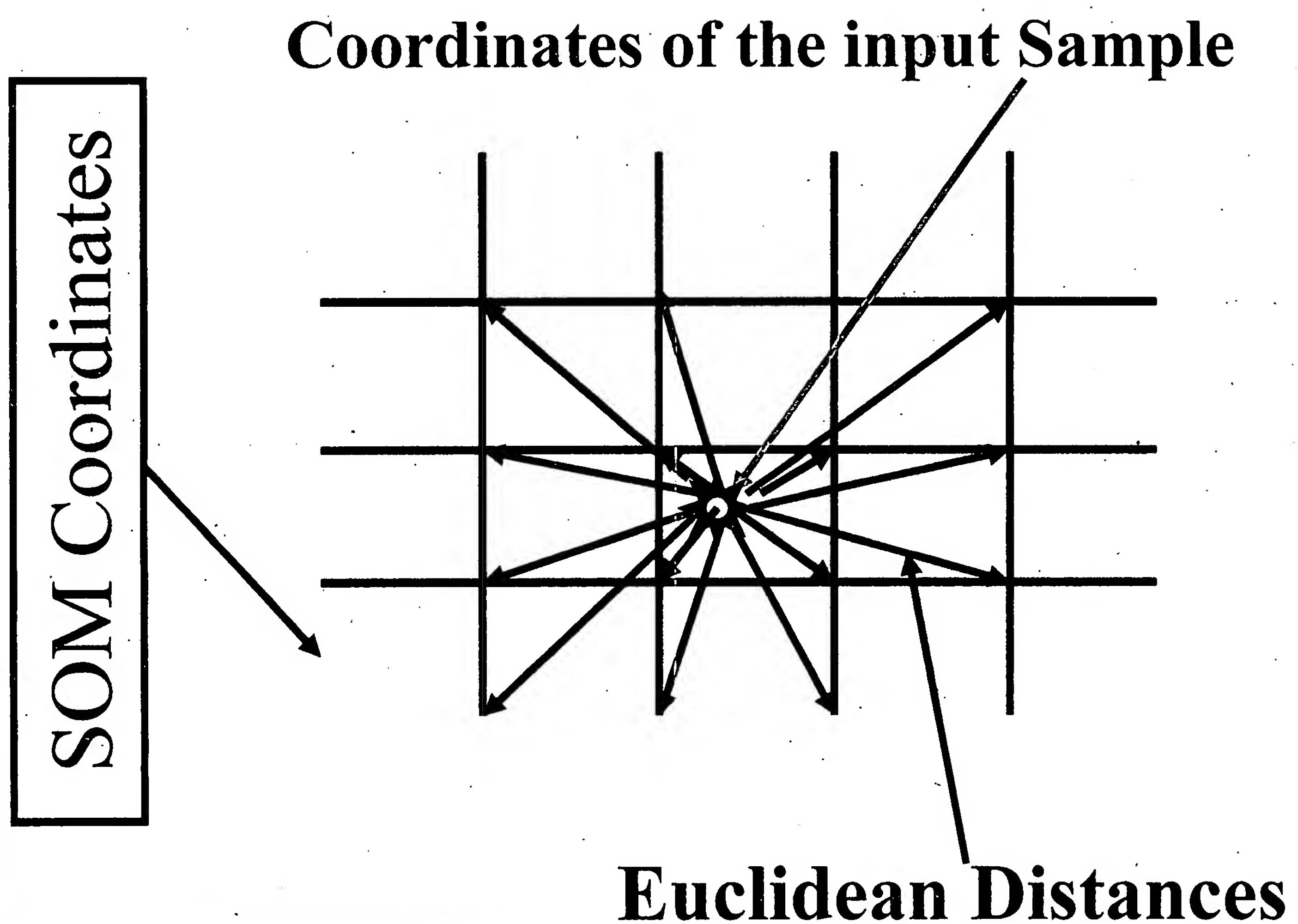


Euclidean Distance between Input and Neural Vectors

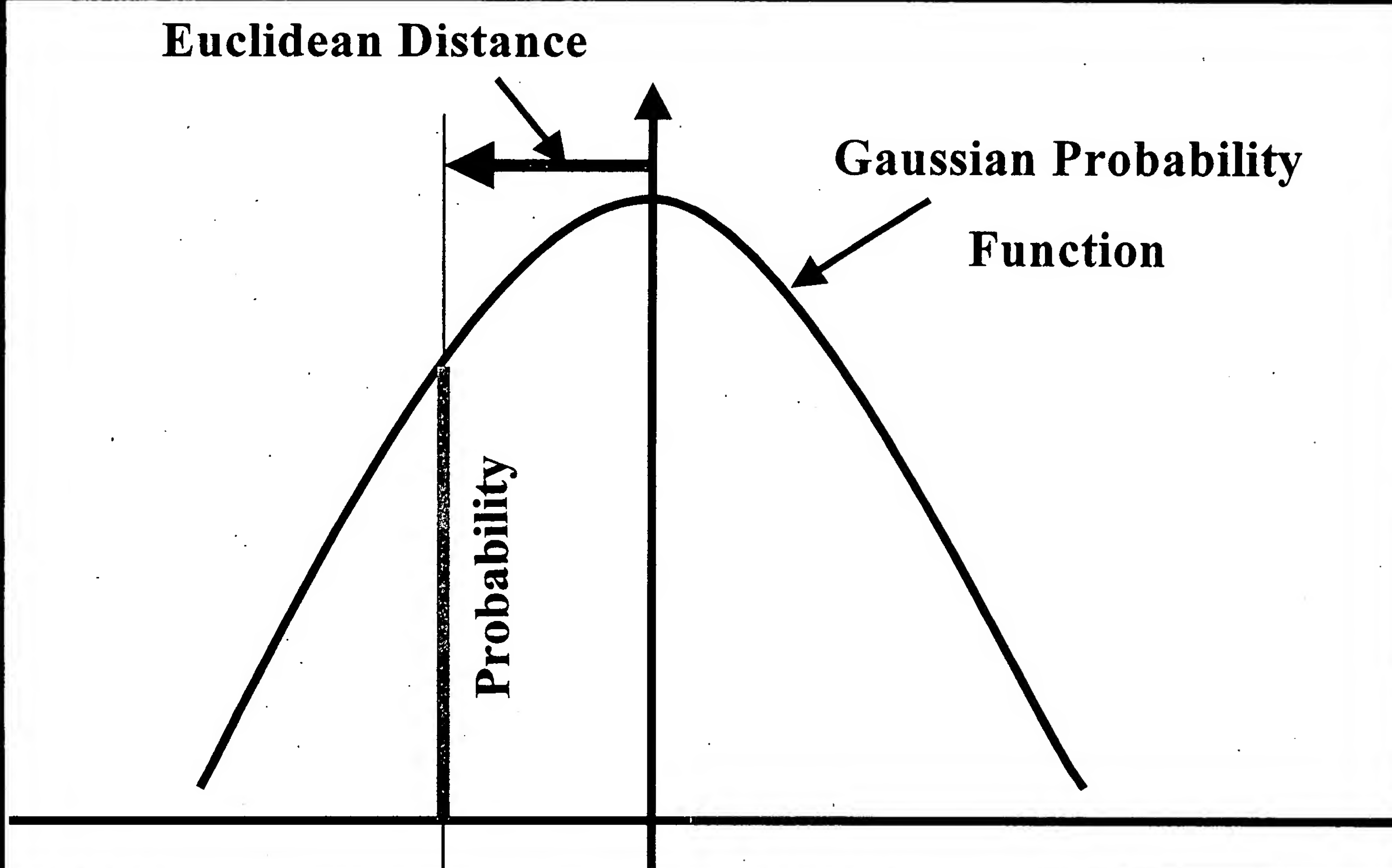


Probability Computation based on a Gaussian Function

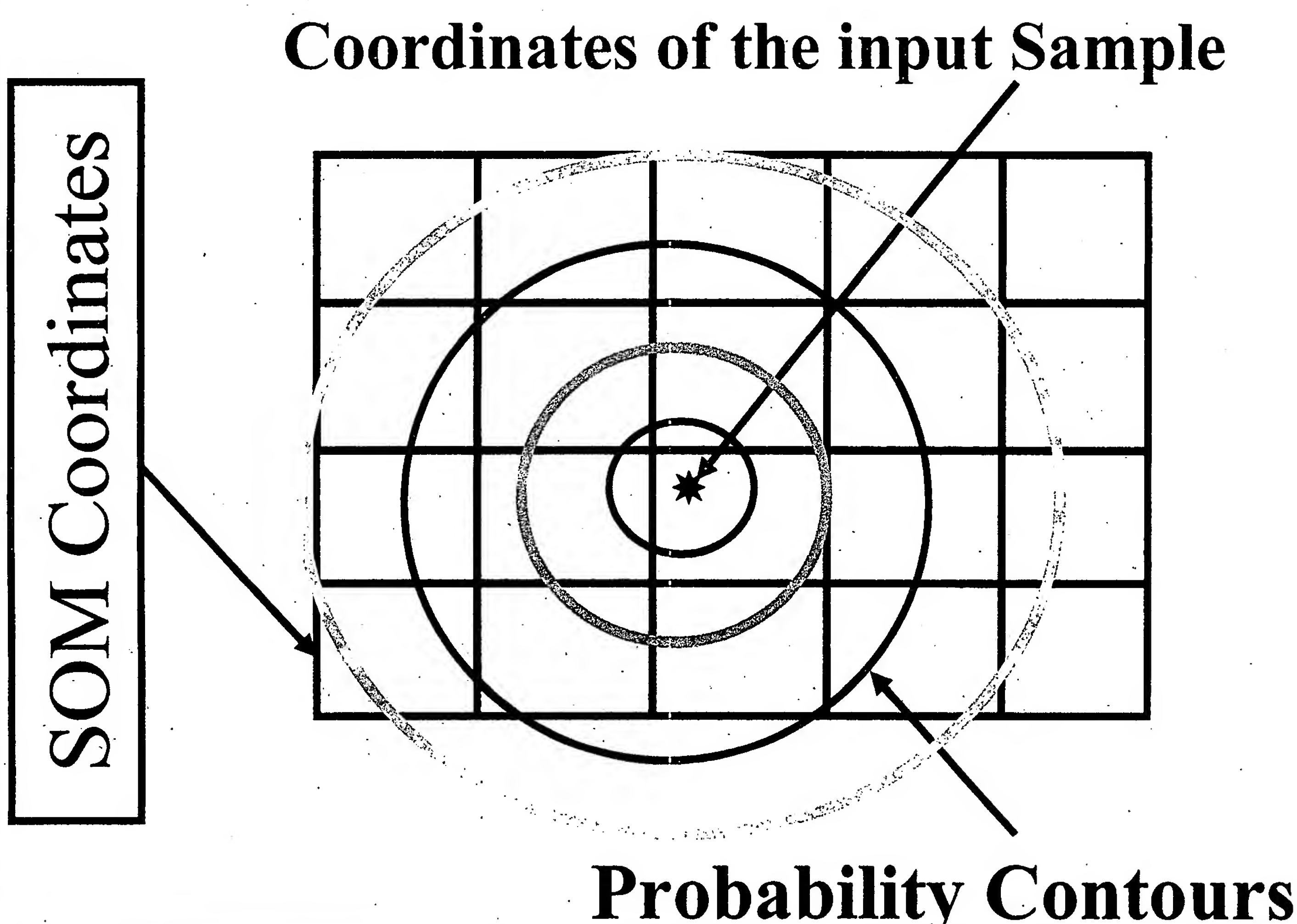

Class A
Probability
Density
Class B
Probability
Density
Bayesian Decision
Boundary



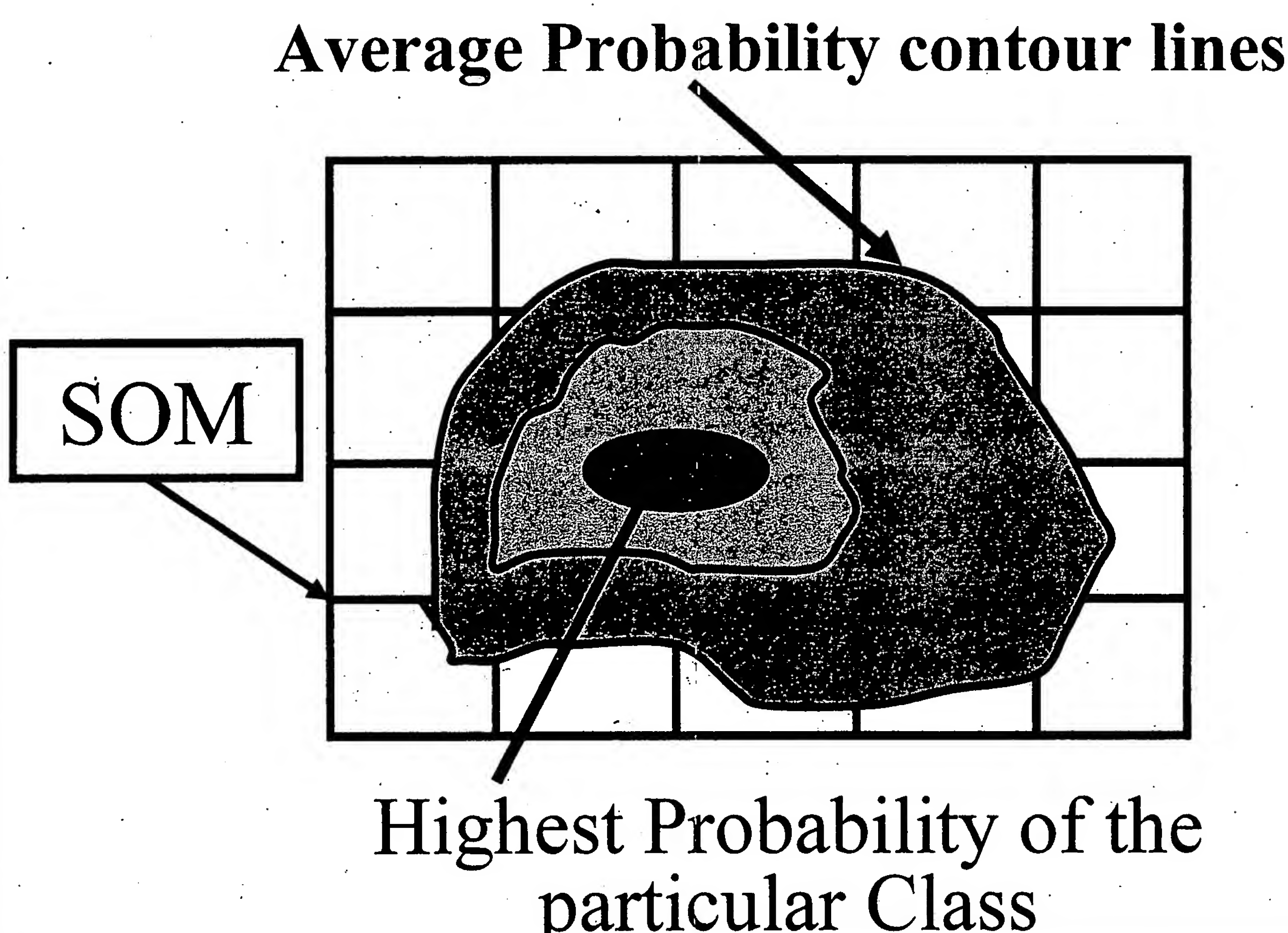
Computation of Probability Densities



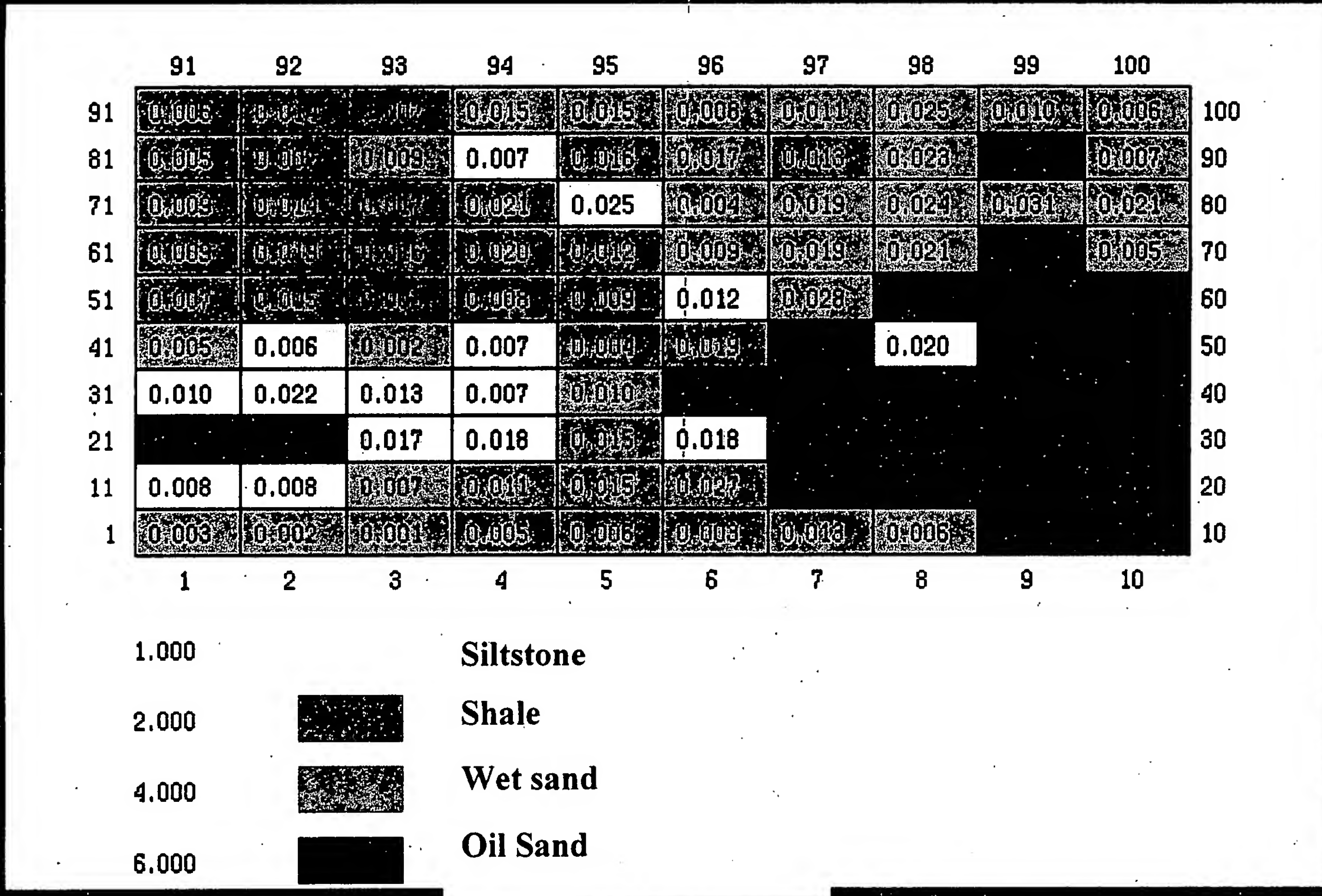
Probability Density Computation based on a Gaussian Function



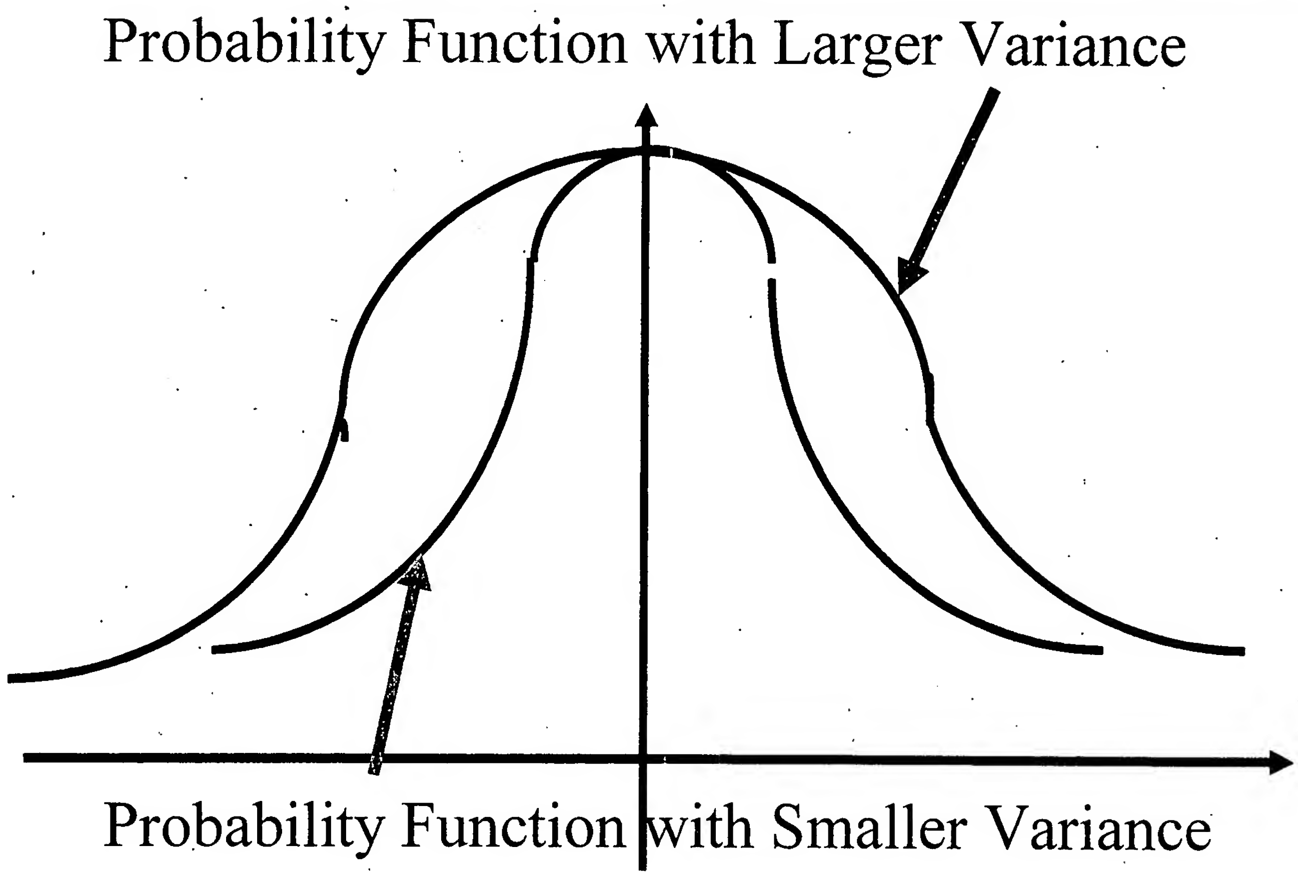
Computation of Probability Densities



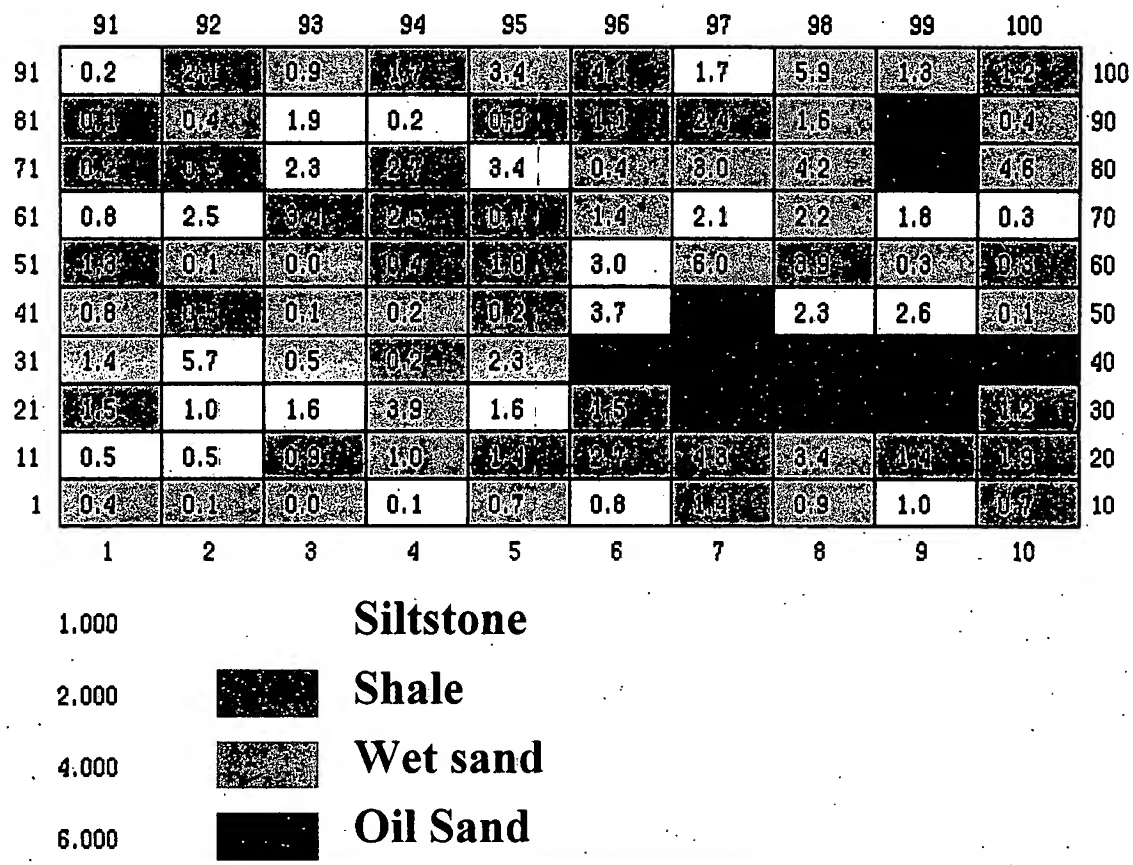
Computation of Probabilities



SOM Calibration for 4 Classes with RMS error variance



Gaussian Probability Functions



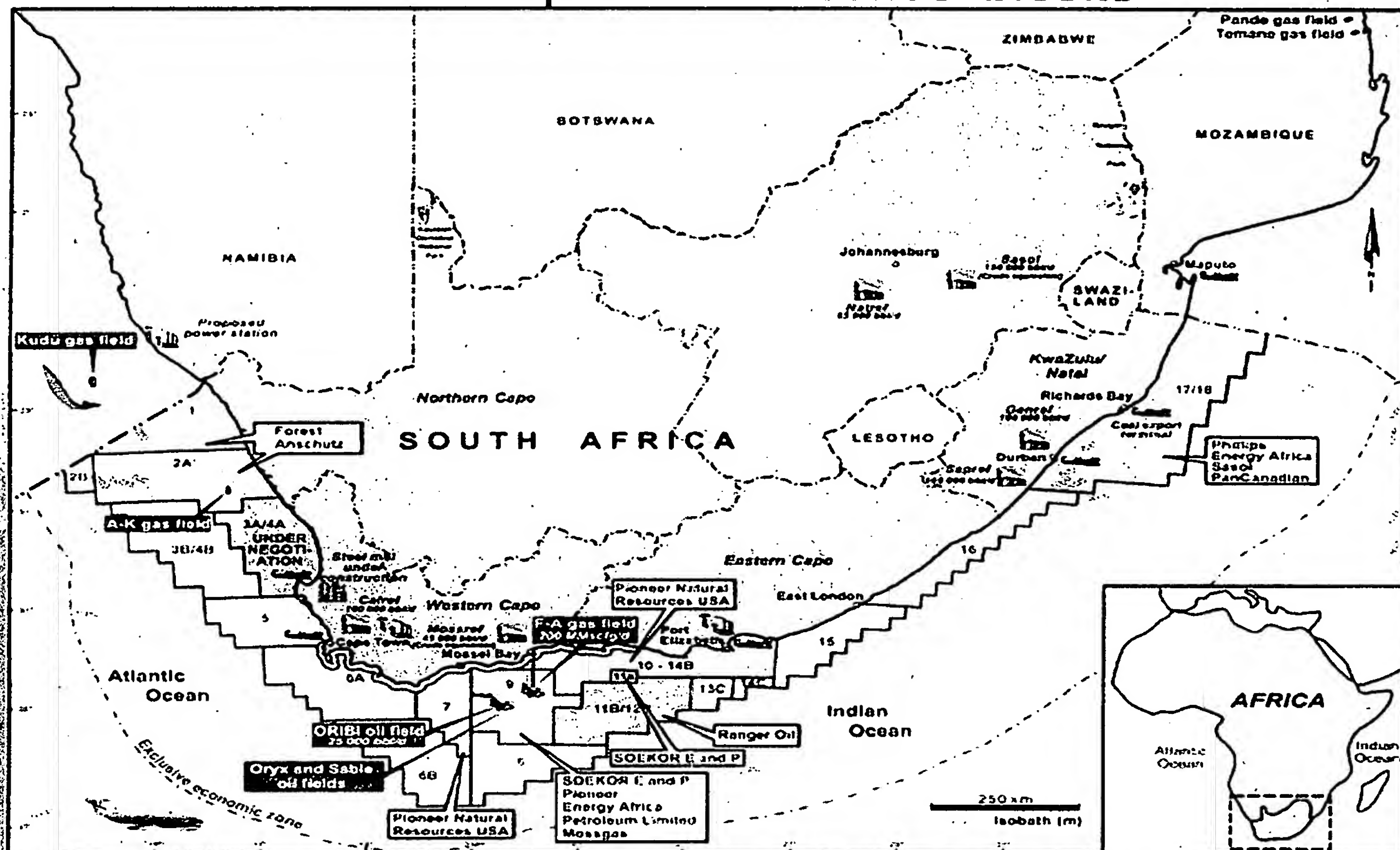
SOM Calibration with Smaller Gaussian Variance

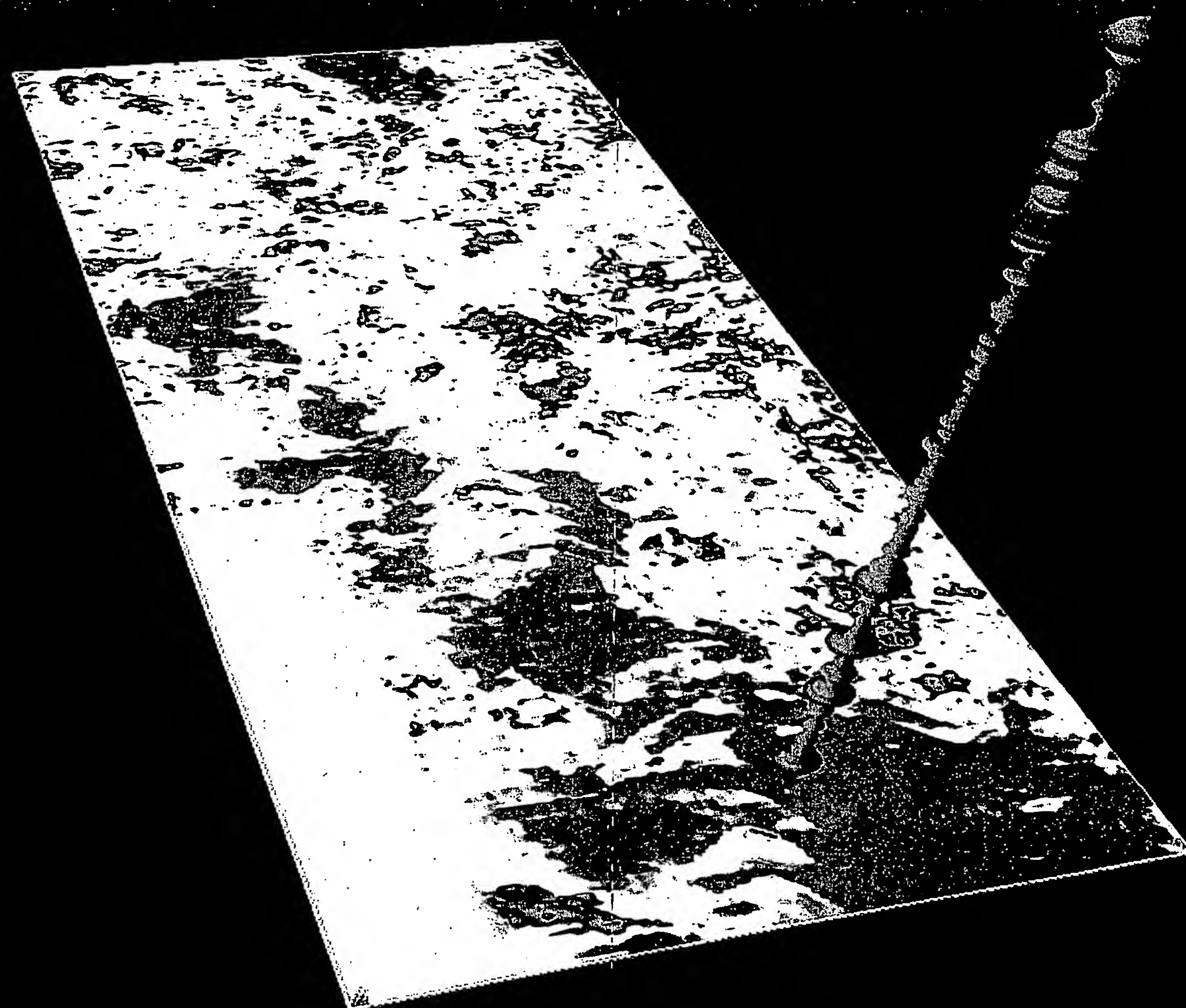
1.000 3.000 5.000 8.000
10.000 12.000 15.000 17.000
19.000 22.000 24.000

	1.0	3.0	5.0	8.0	10.0	12.0	15.0	17.0	19.0	22.0	24.0
1.0	6	1	2	0	1	0	1	1	0	0	0
3.0	13	35	9	9	8	13	3	8	13	5	4
5.0	0	0	3	0	0	0	0	0	1	0	0
8.0	0	0	0	1	0	0	0	0	0	0	0
10.0	0	0	0	0	5	0	0	1	0	0	0
12.0	2	3	1	2	1	4	0	1	0	2	2
15.0	0	1	0	0	1	0	3	0	0	0	0
17.0	0	0	0	0	1	0	0	6	2	2	2
19.0	3	1	1	0	0	0	1	1	12	0	0
22.0	0	0	0	0	0	0	0	0	0	2	0
24.0	1	1	0	0	0	0	0	0	0	0	4

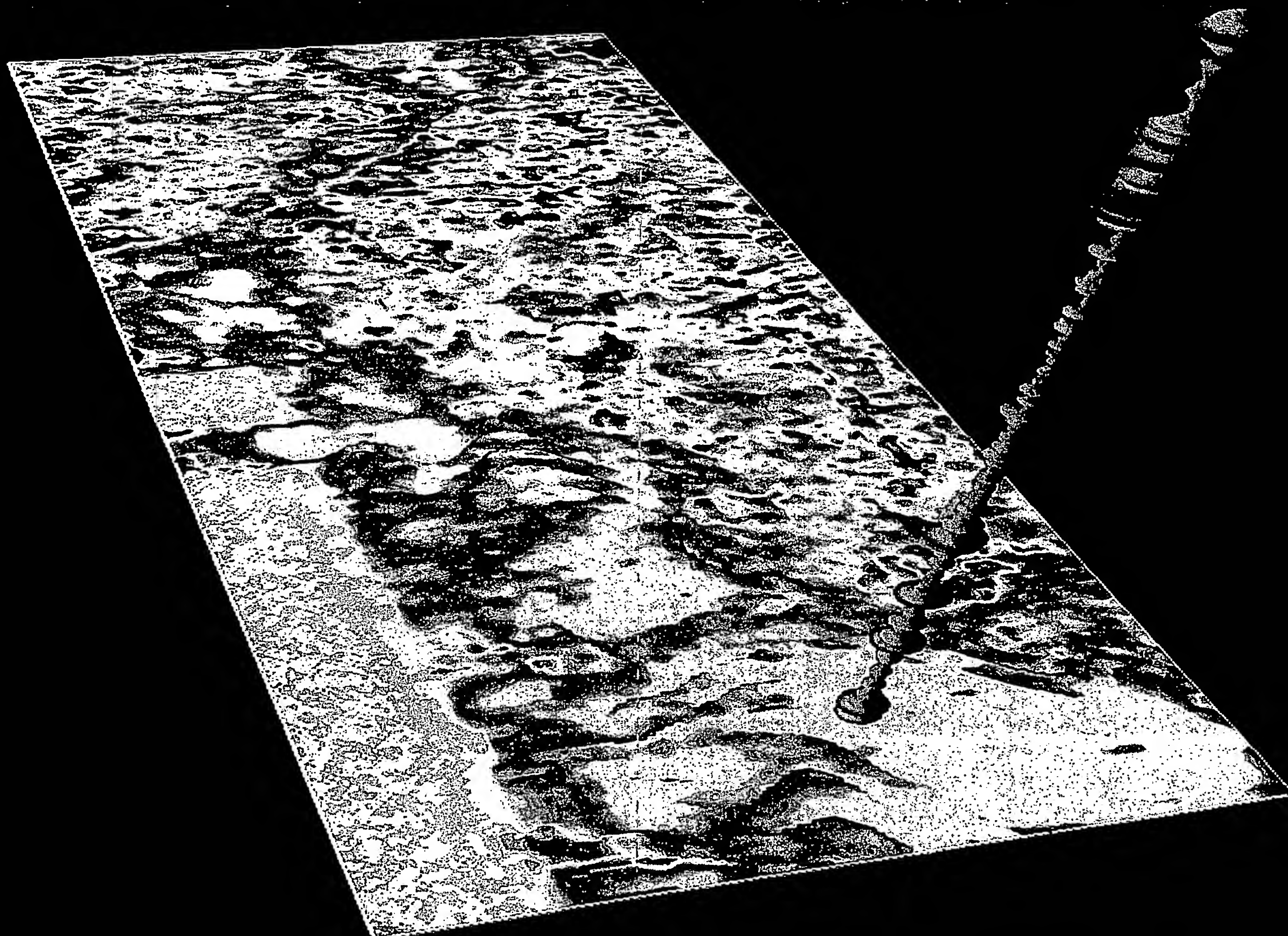
Verification of Calibration
11 Classes

Offshore exploration licence blocks

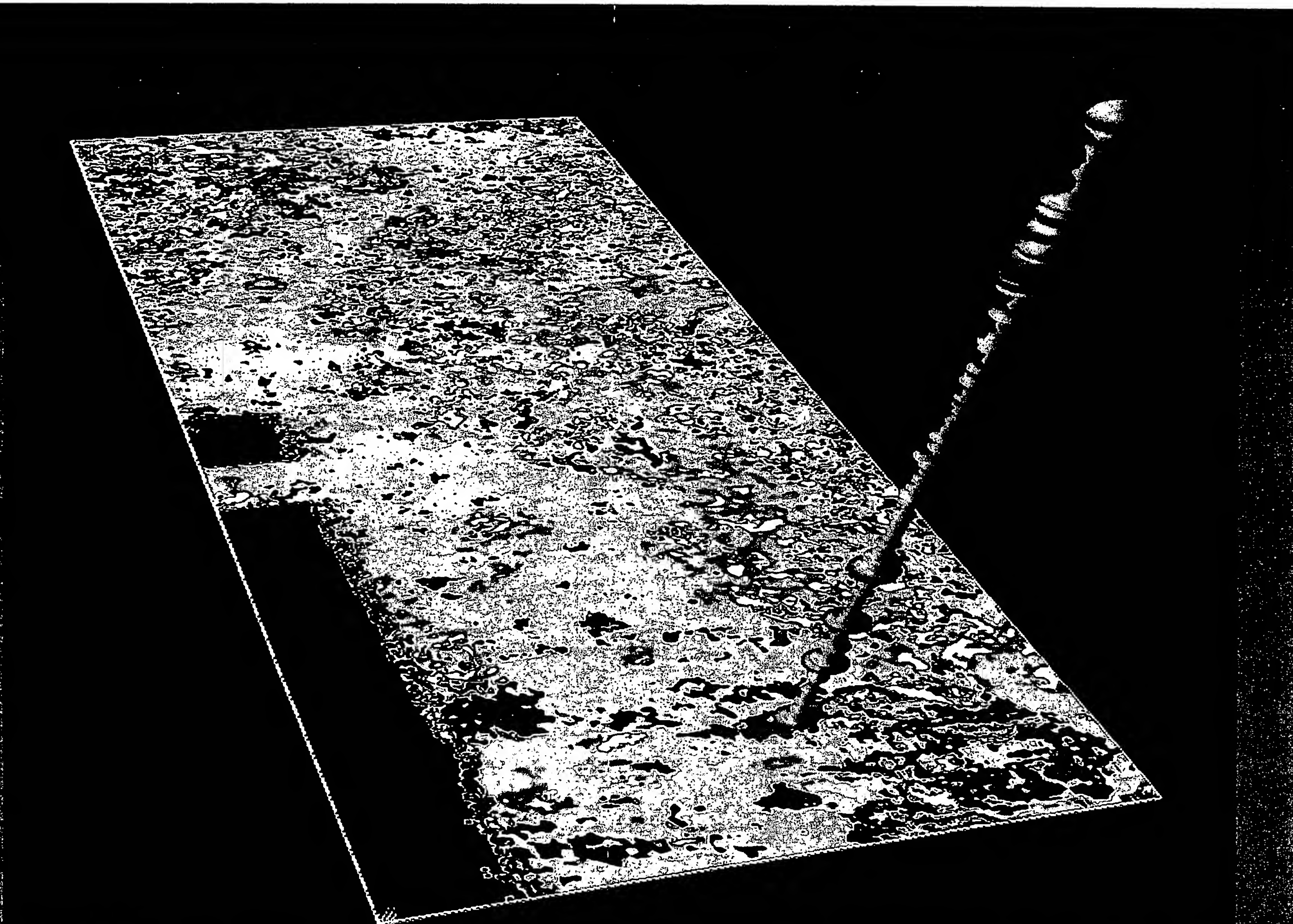




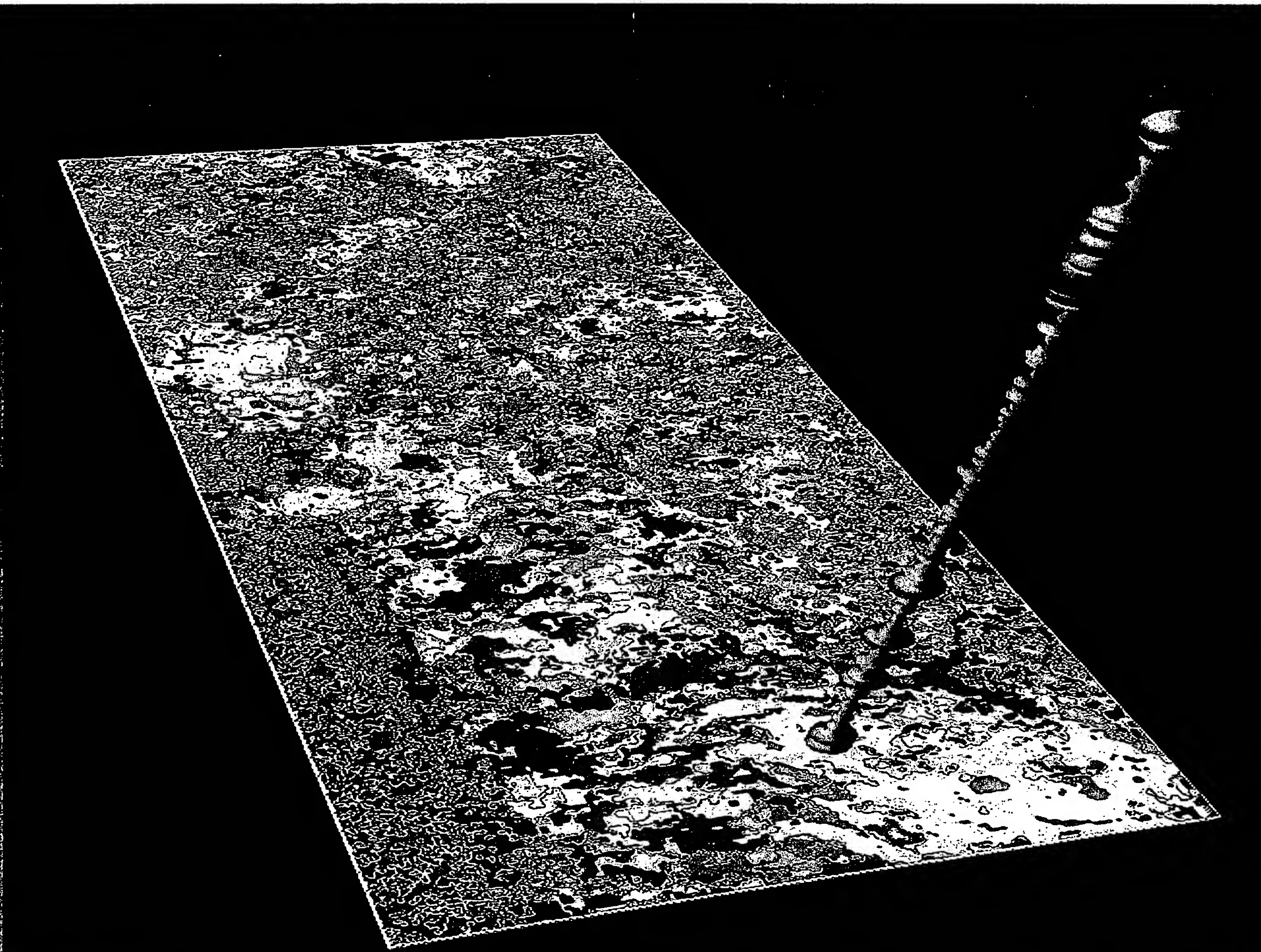
Reservoir Level Time Slice – Amplitude



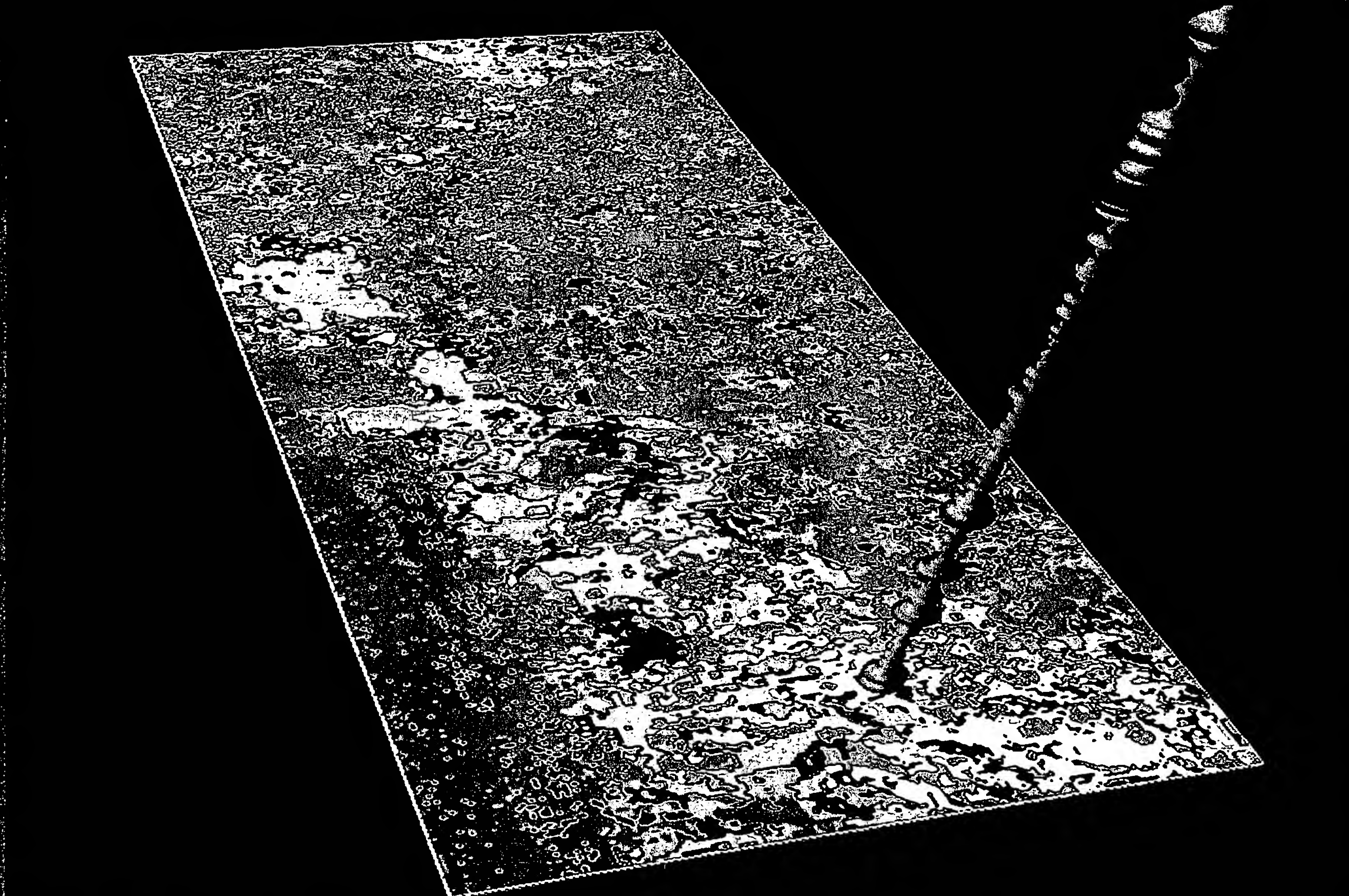
Reservoir Level Time Slice – Relative Acoustic Impedance



Reservoir Level Time Slice – Instantaneous Frequency



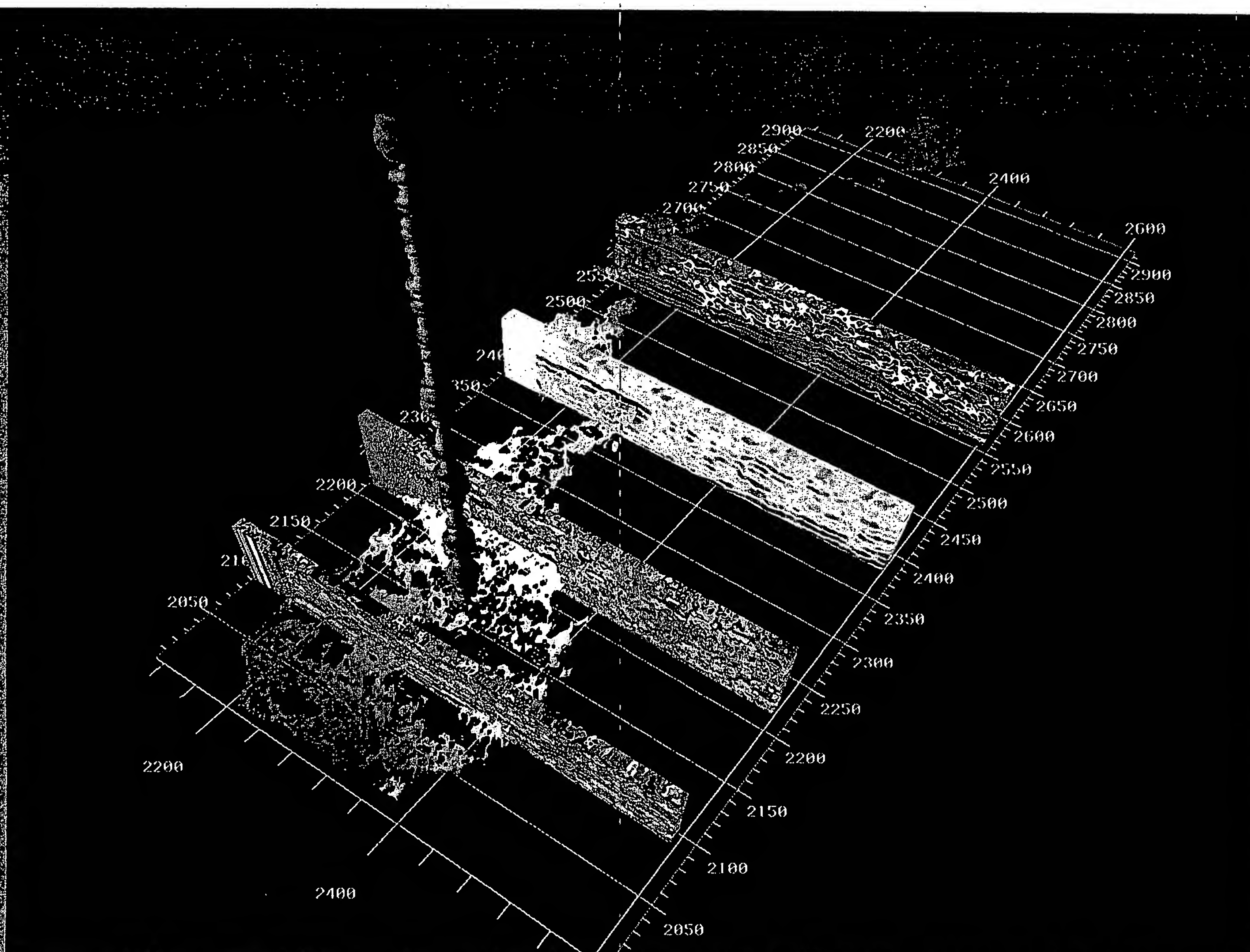
Reservoir Level Time Slice – SOM Clustered Volume (Un-calibrated)



Reservoir Level Time Slice – Calibrated Classification

Rock Solid Images

Combination of Attributes and Classification


2900
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2450
2400
2350
2300
2250
2200
2150
2100
2050
2500
2200
2150
2050
2200
2400

Conclusions

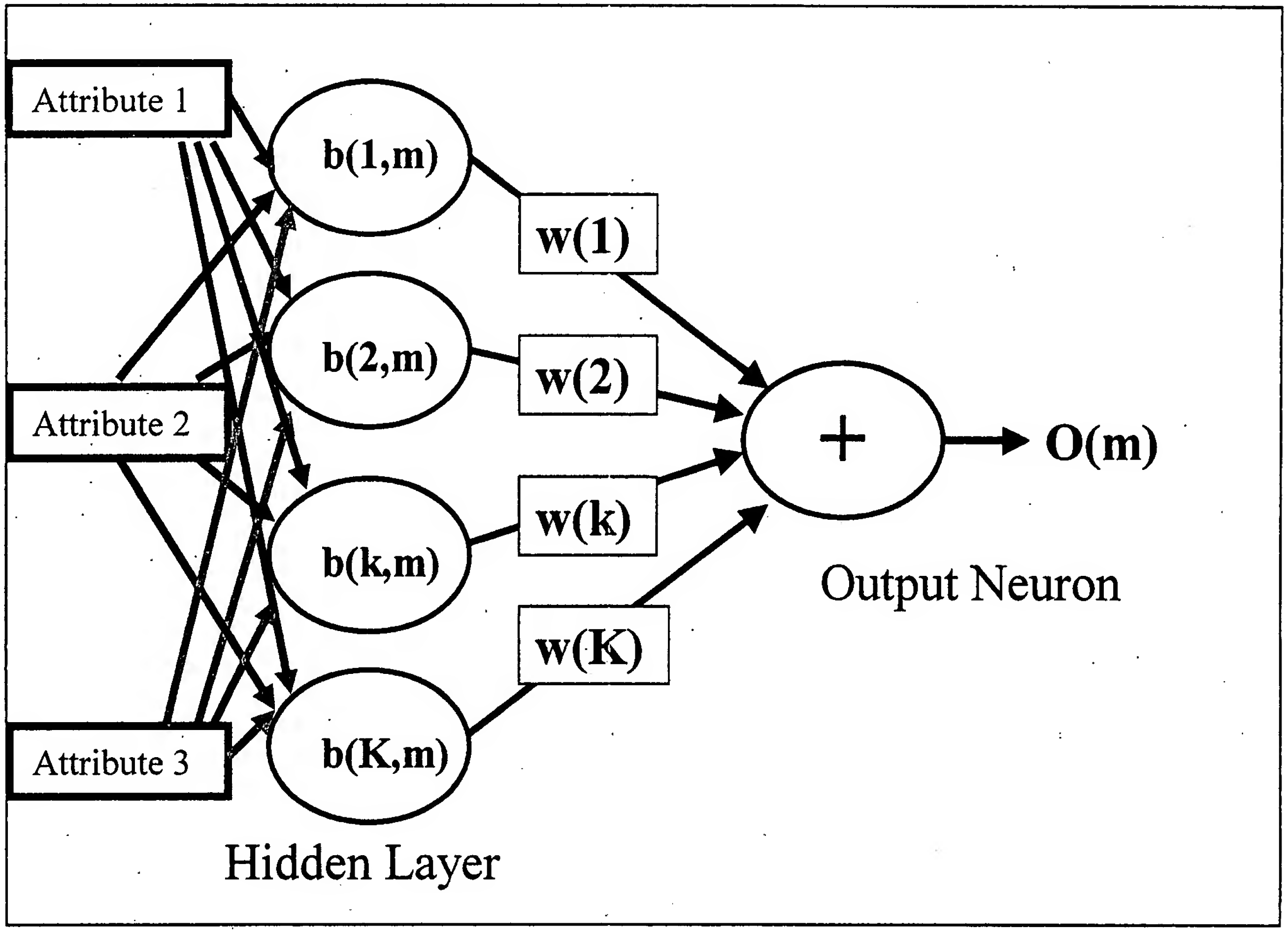
- An unsupervised Kohonen SOM (K-SOM) method has been employed to conduct a multi-attribute based volumetric classification.
- The K-SOM reduces N-dimensional data into a simple, interpretable 2-D cluster map.
- The relationship between cluster centers and lithology or reservoir characteristics derived directly from well logs can be established via a Bayesian logic approach.
- The method is very fast and easily automated.
- In the example shown the classification of gas & water sands follows known channel geometries.

Acknowledgement:

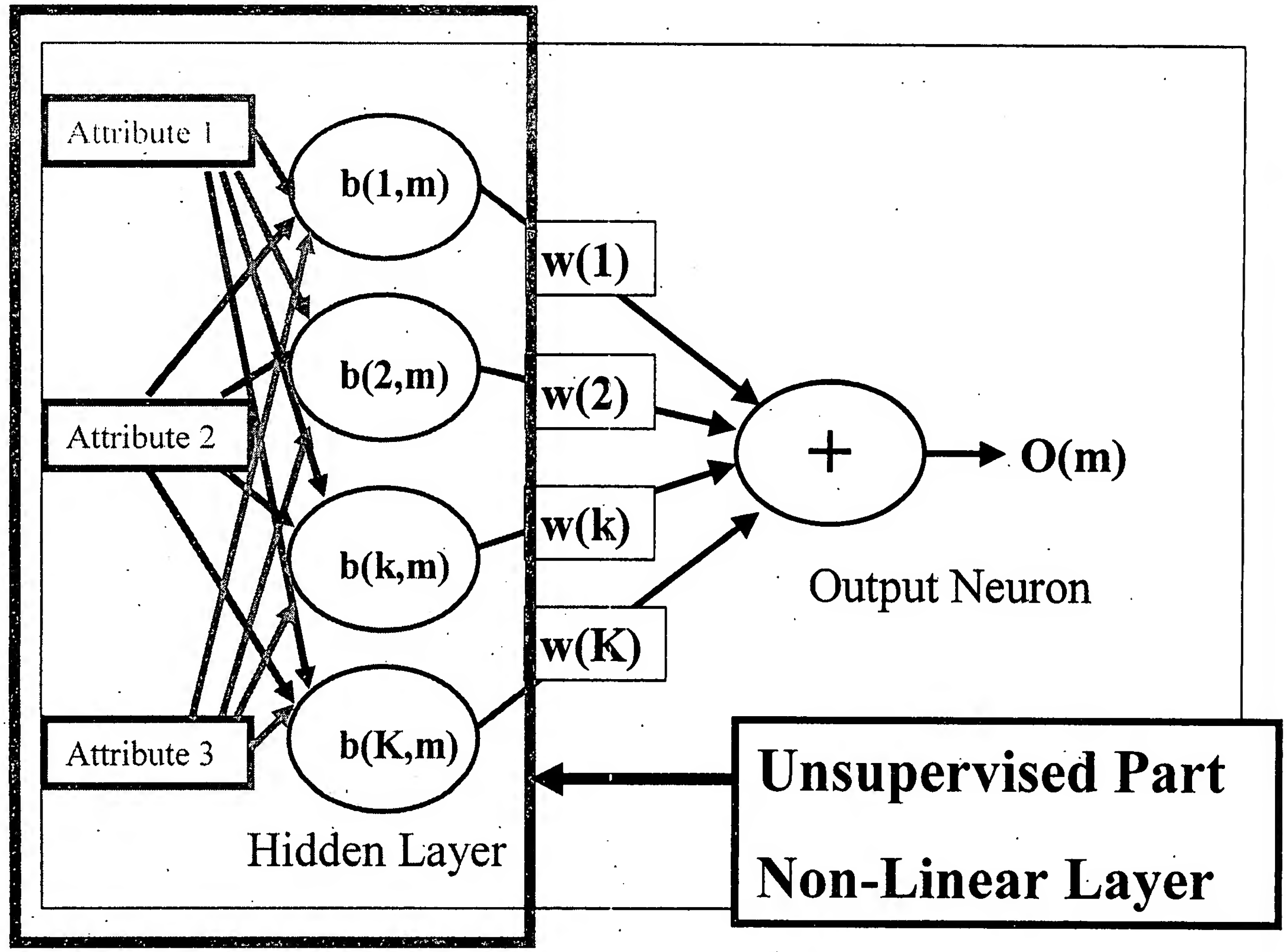
We would like to thank Forest Oil Corporation, Anschutz Corporation, SOEKOR and Petroleum Agency SA for the contribution of the seismic and log data used in this work. We would also like to thank Tim Berge of Forest Oil for his support and technical assistance and Magic Earth for the use of the GeoProbe visualization and interpretation software.

SOM Calibration by RBF Network

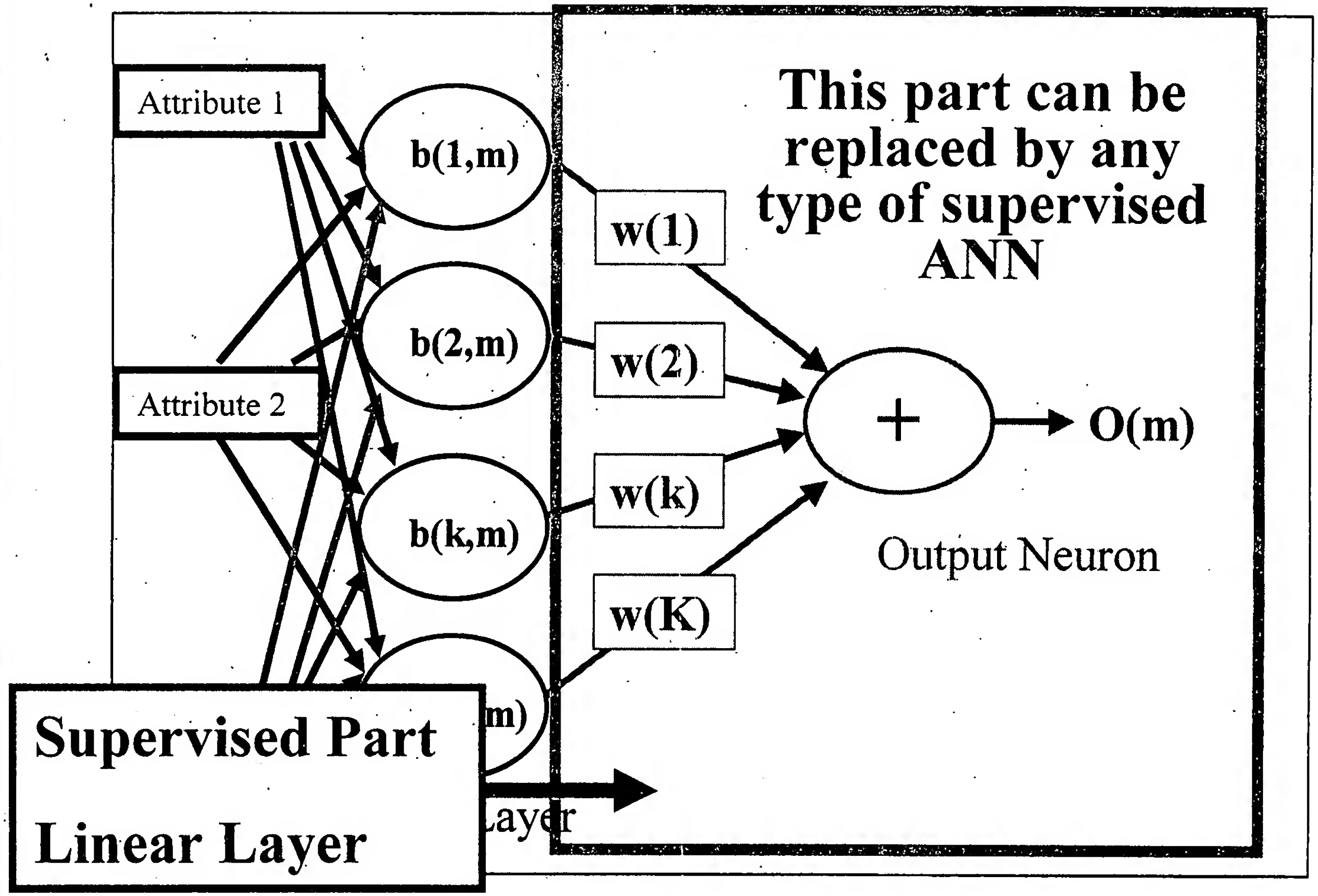
- SOM determines the coordinates of the Neurons in the data input space in an organized manner,
- Conscience algorithm assures the neural centers are placed equi-probability manner,
- SOM neurons can be considered as the hidden layer neurons of RBF network
- RBF network output training and weight computation can be done independently in a supervised manner,
- SOM neurons and computed output layer neural weights can be used as a RBF network for calibrated classifier.



A Typical Radial Basis Function Network Configuration



Radial Basis Function Network Characteristics



Radial Basis Function Network Characteristics

Problems Associated with Calibration

- SOM clustering will depend only on the given set of attributes, proper selection of attributes,
- Time tie with seismic data and corresponding lithology classes,
- Proper definition of lithology classes (we are mixing apples and oranges! Lithology definition varies considerably between well bore and seismic dimensions),
- Check verification, update lithology definition, iterate,
- In younger depositional environment, lithology versus attributes relations may change with depth,
- Results are probabilistic, degree on uncertainty will depend on many parameters, such as processing , velocities and imaging and etc.

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